Two Essays on Strategic Human Resources Management

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Dedication

To Pouyan, who is my everything.

به پویانم :

ای زندگی تن و توانم همه تو

جانی و دلی، ای دل و جانم همه تو

تو هستی من شدی، از آنی همه من

من نیست شدم در تو، از آنم همه تو.

- مولانا

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Chapter 1: Introduction

In the modern knowledge-based economy, the most crucial source of sustainable competitive advantage is human capital resources (Becker & Huselid, 2006; Campbell, Coff, & Kryscynski, 2012). Thus, it comes as no surprise that much attention has being paid to the optimization of human capital resources in both research and practice. Researchers of strategic human resource (HR) management examine the way in which strategic HR practices can help to optimize human capital resources and improve work outcomes (Crook, Todd, Combs, Woehr, & Ketchen, 2011). Examples of these HR practices include employee selection processes to improve the quality of human capital inflow, employee training programs to keep skills up to date, dismissal of poor performers to improve the net quality of human capital resources, and layoffs to increase the efficiency of these resources.

In this dissertation, I focus on employee selection and staffing decisions made to optimize human capital resources in two distinct settings: public education (Chapter 2) and retail (Chapter 3). I examine the consequences of these HR decisions in terms of individual-level (Chapter 2) and unit-level (Chapter 3) outcomes. I draw on the recent developments in the literature on human capital resources and adopt a multidisciplinary approach that bridges scholarships in organizational psychology and personnel economics. I also apply a series of complex and rigorous analytical strategies to bridge scholarship in organizational behavior and personnel economics (i.e., machine learning and Heckman selection method (Chapter 2) and cross-lagged analysis and panel vector autoregression method (Chapter 3)).

In general, both essays in this dissertation are informed by the resource view of human capital that conceptualizes human capital resources as “individual or unit-level capacities based on individual knowledge, skills, abilities, and other characteristics (KSAOs) that are accessible for unit-relevant purposes” (Ployhart, Nyberg, Reilly, & Maltarich, 2014, p. 371). Ployhart et al. (2014) emphasized that researchers should move beyond the bifurcation of human capital into general and specific domains and instead focus on the foundation of human capital resources that resides at the individual level; the knowledge, skills, abilities, and other characteristics (KSAOs) brought to the organization by individual employees.

1.1 Essay One: Using Machine Learning to Translate Applicant Work History into Predictors of Performance and Turnover

In the first essay, my approach is largely informed by research and theories that call for the development of fair and reliable strategic HR practices to improve the quality of human capital resources while lowering the risk of adverse impact. Acknowledging that the foundations of unit-level human capital resources reside in individuals’ KSAOs (Ployhart, Nyberg, et al., 2014), I and my co-authors adopt a micro approach to studying the optimization of human capital resources through strategic employee selection. We use machine learning to translate pre-hire signals in applicants’ work histories into reliable, accurate, and fair predictors of their subsequent performance and turnover. Work history information reflected in résumés and application forms is commonly used to screen job applicants. However, there is little consensus as to how to systematically translate information about a person's past into predictors of future work outcomes. In this paper, we apply machine learning techniques to job application form data (including previous job descriptions and stated reasons for changing jobs) to develop measures of work experience relevance, tenure history, history of involuntary turnover, history of avoiding bad jobs, and history of approaching better jobs. We empirically examine our model on a longitudinal sample of 16,071 applicants for public school teaching positions and predict subsequent work outcomes, including student evaluations, expert observations of performance, value-added to student test scores, voluntary turnover, and involuntary turnover. We find that work experience relevance and a history of approaching better jobs are linked to positive work outcomes, whereas a history of avoiding bad jobs is associated with negative outcomes. We also quantify the extent to which our model can improve the quality of the selection process relative to conventional methods of assessing work history, while lowering the risk of adverse impact.

1.2 The Impact of Organizational Context on the Relationship between Staffing Events and Work Outcomes: Where Parallel Universes Meet

In the second essay, I adopt a macro approach to investigate the way in which changes to a unit's human capital resources, either through HR-initiated staffing events (i.e., hiring, employee dismissal, or layoff) or employee-initiated events (i.e., voluntary turnover) can influence workplace outcomes over time and in relation to various internal and external workplace contextual factors. This study is mainly motivated by research and theories that call for a temporal, dynamic, and holistic examination of the interactions between staffing, work outcomes, and contextual factors. I draw on Context-Emergent Theory (CET) (Nyberg & Ployhart, 2013), which is a based on the resource view of human capital. CET theory conceives of human capital flow as a dynamic and holistic process. It also accounts for the moderating effects of context on the relationship between collective turnover and work outcomes.

To empirically evaluate my research questions, I use longitudinal personnel, financial, and pulse survey data collected from 1,837 stores (work units) of a large national retailer. I examine the duration and significance of effects of staffing events on work outcomes by considering the components of my model as endogenous, co-evolving parts of a dynamic system whose effects interact and unfold over time.

This study provides insight to the relationship between human capital flow and workplace performance. Moreover, it shows how contextual factors—both internal and external to the workplace—modify these relationships over time. This research expands the scope of existing studies in the literature by taking into account the reciprocal and dynamic nature of staffing events, context, and workplace outcomes. My assessment of these relationships provides some support for the notion that staffing events impact subsequent unit performance and voluntary turnover rates. However, these effects do not develop in parallel over time and differ under varied contextual situations.

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Taken together, these essays support the importance of different strategic HR practices in the optimization of human capital resources, both at individual level KSAOs and unit-level human capital. The following essays also demonstrate the way in which changes in human capital resources can shape individual and workplace outcomes. Moreover, these studies support the notion that HR practices can have different effects on outcomes over time, based on the contexts in which they take place.

Chapter 2: Using Machine Learning to Translate Applicant Work History into Predictors of Performance and Turnover

Sima Sajjadiani, Aaron Sojourner, John Kammeyer-Mueller, Elton Mykerezi

2.1 Introduction

Researchers and practitioners continuously work to take advantage of massive databases of job applications produced by fully electronic application systems. These systems present challenges, as organizations need to contend with a very large number of applicants in a systematic and efficient manner (Flandez, 2009; Grensing-Pophal, 2017). Both internal HR departments and consulting firms are evaluated based on time-to-hire and volume of qualified candidates (Gale, 2017). To keep the best applicants through the recruiting process, organizations need to respond rapidly to individuals who may be sending out dozens of online applications (Ryan, Sacco, McFarland, & Kriska, 2000). Time pressures, the large volume of applications, the complexity of the decision task, and recruiters' biases, stereotypes, and heuristics increase the chance of overlooking or misinterpreting candidate qualifications. Inaccurate decision processes are especially common when recruiters have to rapidly contend with large volumes of information (e.g., Converse, Oswald, & Gillespie, 2004; Dawes, Faust, & Meehl, 1993; Dipboye & Jackson, 1999; Tsai, Huang, Wu, & Lo, 2010).

While standardized tests and inventories speed the acquisition of data about candidate characteristics, they overlook more individualized applicant information. Work history, including relevant work experience, tenure in previous jobs, and reasons for leaving previous jobs, is empirically and conceptually distinct from either cognitive ability or personality, and so has the potential to add significant predictive power in a selection battery (Ryan & Ployhart, 2014). Although job-relevant experience is a strong predictor of performance, it is difficult to effectively and systematically track this job-relevance across multiple applicants' idiosyncratic work histories (Tesluk & Jacobs, 1998). For example, recruiters might struggle to quantify the difference between an individual who has five years of work experience in a field like childcare relative to someone with three years of experience in a field like corporate training, or to quantify the difference between a person who quit a previous job because of insufficient administrative support versus a person who quit a previous job to follow an intrinsic desire to share knowledge. Lacking a system for organizing this type of job history information, many organizations default to using years of experience in jobs with similar titles or use highly idiosyncratic and cumbersome decision processes to evaluate qualifications.

To circumvent the problems involving large numbers of applications and a need for speed, large-scale data analytic techniques are used to comb through open-ended text fields in applications. Most HR professionals are familiar with automated keyword searches of applications, a method that far predates the use of electronic systems (e.g., Peres & Garcia, 1962). The development of these lists is often ad hoc in nature, and not linked to a conceptual or theoretical understanding of qualifications. In the absence of this knowledge, the cognitive and information limitations of decision makers are built into the system in the stage of building keyword lists (Bao & Datta, 2014). Keywords are often applied in a rudimentary scorekeeping method, with each word that matches the keyword list receiving equal weight independent of the context in which the word is used. As such, there is a need for much more theoretically grounded approach that is less vulnerable to decision making error in system development.

Recent developments in machine learning provide opportunities to summarize work history as rapidly as keyword methods, but in a far more rigorous and comprehensive manner. Broadly defined, machine learning consists of prediction algorithms, including text classification and natural language processing, to classify items into categories or order items based on a criterion (Mohri, Rostamizadeh, & Talwalkar, 2012). Unlike keyword searches, these techniques find terms that co-occur rather than individual words, better incorporating context. Moreover, machine learning calculates the importance of each word for each category and develops an algorithm that calculates the probability that a response fits across multiple categories. This permits a single statement to indicate values across many different variables. Machine learning and text-mining methods are becoming more prevalent in the field of psychology. de Montjoye, Quiodbach, Robic, and Pentland (2013) used phone metadata (e.g., call frequency, duration, location, etc.) to measure users' personalities. Doyle, Goldberg, Srivastava, and Frank (2017) used text mining and computational text analysis to measure the internalization and self-regulation components of cultural fit in organizations by analyzing employee emails over time. However, despite recent calls to apply these methodological developments (Campion, Campion, Campion, & Reider, 2016; Chamorro-Premuzic, Winsborough, Sherman, & Hogan, 2016), to the best of our knowledge, machine learning and text-mining have not been systematically applied in the selection context to translate information from standard application forms into predictors of subsequent work outcomes.

In an attempt to find low-cost and systematically assessed predictors of performance and turnover from applications, we use recent developments in machine learning to develop novel and indirect measures of different aspects of work history. Work history in application forms focuses on three main aspects, (1) applicant's work experience relevance incorporating correspondence of knowledge, skills, abilities, and other attributes (KSAO) information from previous job titles and job descriptions with the current job, (2) tenure history, which incorporates length of tenure in previous jobs, and (3) attributions for previous turnover, including a history of involuntary turnover, avoiding bad jobs, and approaching better jobs. This is an especially robust mix of predictors, representing components of skill development, patterns of behavior and attitudes, and general motivation for work. We rely on theories related to approach-avoidance motivation (Elliot, 1999; Elliot & Thrash, 2002, 2010; Higgins, 1997; Maner & Gerend, 2007; Neumann & Strack, 2000) to explain why avoiding bad jobs or approaching better jobs, especially when repeated over time, sends signals about applicants' relatively stable characteristics. These pre-hire measures are used to predict subsequent performance across multiple domains, and both voluntary and involuntary turnover hazards (i.e. duration of employment until turnover occurs). The method of machine learning allows us to provide a rich and systematic representation of applicant's experience in jobs, as well as their general orientation toward work, while still emphasizing predictors that are verifiable and highly acceptable to applicants and organizations alike. Our machine learning system is evaluated in the Minneapolis Public School District (MPS) on a sample of 16,071 applicants for 7 teaching job categories over 7 years.

Besides these innovations on the predictor side, we are able to evaluate the proposed selection system using a broad set of outcome variables, and contrast this idealized system relative to existing systems. Barrick and Zimmerman (2009) opened out the criterion space to include both performance and turnover, and concluded that it is more cost-effective for organizations to assess candidates using constructs that predict both performance and turnover. Unfortunately, many of the efforts to identify predictors of distinct task performance dimensions have proceeded in a piecemeal fashion, rather than considering how to optimize selection across the different outcomes. Our data allow us to address these concerns by incorporating multiple perspectives on performance, including (1) student evaluations of teachers, (2) expert observations of performance, (3) value-added changes in student test scores over the course of the school year, and (4) voluntary and involuntary turnover hazards.

2.2 Linking Work History to Performance and Turnover

Most standard application forms request information related to work experience and history of job changes. In addition to these factual pieces of information, forms also frequently ask applicants questions related to their previous jobs, their tenure in those jobs, and reasons for leaving those previous jobs. Below we describe how we use these clues in work history to assess how well-acquainted applicants are with task characteristics, learn about their behavioral tendencies linked to turnover, and infer their overall orientation toward work.

2.2.1 Relevant experience

Work experience is conceptualized in terms of whether the applicant has encountered work situations relevant to the requirements of the job for which s/he applies. Ployhart (2012, p. 24) proposed that “work experience is a broad, multidimensional construct that often serves as a proxy for knowledge”. Quiñones, Ford, and Teachout (1995) and Tesluk and Jacobs (1998) emphasized the importance of the qualitative aspects of work experience, including the type of tasks performed which can be translated into work-related knowledge and skills. Relevant job experiences are also considered socially acceptable as hiring criteria by job seekers, organizations, and legal systems because they are factual and task related. The likelihood of providing misleading information regarding work history also goes down if work experience is verifiable (Brown & Campion, 1994; Cole, Rubin, Feild, & Giles, 2007; Knouse, 1994; Ployhart, 2012; Waung, McAuslan, & DiMambro, 2016).

Mechanisms that might tie experience to work performance involve acquisition of knowledge and skills, knowledge of occupational norms, and self-selection. The key factor here is work experience relevance, which we define consistent with prior work (e.g., Dokko, Wilk, & Rothbard, 2009) as the degree of correspondence between the required knowledge, skills, abilities, and other characteristics of applicants’ previous jobs and the focal job. Relevant experience has several key features that would make it uniquely predictive of subsequent performance and turnover. KSAO-based matching of experience is a better predictor of job performance than using a simple assessment of titles from previous jobs, or relying on applicants' or recruiters' estimation of whether and how long the applicants had relevant work experience (Quińones et al., 1995). The training and development literature (Blume, Ford, Baldwin, & Huang, 2010; Saks & Belcourt, 2006) argues that employees develop job proficiency by repeatedly doing tasks that are contextually similar to those done on the job. Some prior work has shown that resumes hand coded at the occupational level are predictive of job performance as mediated through acquired skills and knowledge (Dokko et al., 2009).

Relevant work experience also signals applicant's fit with the focal job and their subsequent duration of employment. Via self-selection processes, applicants who have had relevant work experience previously make more informed decisions relative to those who have not had such direct interaction with core job tasks (Jovanovic, 1984). These informed decisions are expected to result into higher level of performance and lower risk of voluntary turnover. Adkins (1995) argues that those who have had similar work experience also adjust more quickly because they have a more accurate set of expectations regarding working conditions.

Several studies show that individuals often gravitate toward the jobs that match their KSAOs better (Converse et al., 2004; Wilk, Desmarais, & Sackett, 1995; Wilk & Sackett, 1996). Also, research shows that tenure in the job impacts human capital accumulation (Gibbons & Waldman, 1999; Kuhn & Jung, 2016; Mincer & Polachek, 1978). Therefore, we believe that tenure in each previous job and time elapsed since each previous job also provide valuable information about applicants' level of acquired knowledge, skills, abilities, interests, and values in their past work experiences. In operationalizing work experience relevance, we take into account these factors in conjunction with the similarity between the KSAOs required for each previous job and the job for which the applicant applied.

Despite the significant theoretical importance of relevant experience, there are still few efforts to build a truly systematic scoring method for evaluating work experience relevance in the literature. Large databases of job titles and relevant tasks have a long history of being used in the development of selection measures in organizational psychology, as shown in research on synthetic validation (Johnson et al., 2010; Steel & Kammeyer-Mueller, 2009). Such tools are used to assess the validity of employment tests, but not for evaluating performance.

Assessing job similarity or work experience relevance systematically is also challenging for many organizations, leaving selection decision makers to use guesses and inferences about how relevant each job is to the current position. Many studies that address work history to measure applicant's relevant experience operationalize it by the length of tenure in the same occupation or in the same organization (e.g., Adkins, 1995; Sturman, 2003). In this study we propose a new way to measure the similarity between applicants' past work experience and the requirements of the focal job more systematically. Here, we use machine learning to create a rigorous model of work experience relevance by matching the required KSAOs assessed in O*NET to the relevance of the experiences found on the job. We operationalize work experience relevance by measuring the similarity between the KSAOs required for applicants' previous jobs and the required KSAOs for the job for which the applicant has applied. We categorize previous jobs' self-reported titles and job descriptions provided by the applicants in their application form into the standard O*NET occupations. Then, we use profile analysis techniques to measure the similarity between applicant's past profile and the profile of the focal job. As a machine learning technique, words from self-described job titles and job descriptions are matched with best fitting O*Net job titles probabilistically, so an occupation match can be linked across a variety of O*Net job titles even when they do not exactly match those in the database. From these probabilities, the level of different work characteristics the individual has encountered in previous jobs can be estimated. We also take into account the tenure in each previous job and the recency of each job in building applicant's work experience relevance. In sum, we believe that this machine learning approach will create a systematic, meaningful, and theoretically grounded assessment of applicants' relevant work experience.

> ***Hypothesis 1:*** *Work experience relevance, assessed through machine learning, is (a) positively associated with teacher performance and (b) negatively associated with turnover hazard.*

2.2.2 Tenure History

There is a consensus among organizational psychology and human resource management researchers and practitioners that past behavior is the best predictor of the future behavior (Barrick & Zimmerman, 2005; Owens & Schoenfeldt, 1979; Wernimont & Campbell, 1968). One of the key bits of information regarding behavioral tendencies that can be drawn from a job application form is the applicant's average length of time spent in previous jobs, which we term “tenure history.” A person with a questionable tenure history might have a record of changing jobs after a relatively short period of time, whereas a more reliable tenure history would be indicated by many spells of long tenure in previous jobs. The relevance of prior tenure for predicting future tenure was recognized by Ghiselli (1974), which he attributed to a dispositional impulsivity and an almost uncontrollable need to change jobs. The existence of different typical levels of tenure history across jobs has been noted in several subsequent theoretical and empirical works (e.g., Judge & Watanabe, 1995; Maertz & Campion, 2004).

Moreover, Barrick and Zimmerman (2005) found that if one expresses a habit of seeking out other jobs—represented by a short tenure in one’s previous jobs—one is likely to do so again in one’s next position. They explained that “while most turnover models view intent to quit as an immediate precursor to actual turnover, some individuals may be predisposed to quit even before starting the job” (Barrick & Zimmerman, 2005: 164). Peripatetic tenure history could also signal problems in other areas of work behavior. Job applicants with poor levels of skills or motivation are expected to have lower average tenure in their previous jobs as they either involuntarily leave the position (i.e., get terminated or laid off due to their weak performance) or otherwise voluntarily leave the job because they lack dispositional conscientiousness for their work (Barrick & Zimmerman, 2009; Griffeth, Hom, & Gaertner, 2000; Judge, Thoresen, Bono, & Patton, 2001). Other researchers argued that short tenure in previous jobs may reflect a poor ethic, correlated with consistently lower levels of organizational commitment and a higher likelihood of turnover (Mathieu & Zajac, 1990).

Hypothesis 2: *Tenure in previous positions is positively related to (a) teacher performance, and negatively related to (b) voluntary and (c) involuntary turnover hazard.*

2.2.3 Attributions for Previous Turnover

Our use of machine learning is uniquely suited to examining open text attributions for leaving jobs. A key assumption underlying our own model is that reasons for turnover extracted from job applications are indeed a valid signal of traits and dispositions toward work. This approach to coding written text as indicative of stable characteristics has a long history (F. Lee & Peterson, 1997), and despite the subjectivity of coding, these projective measures have shown some validity in predicting behavior (e.g., Spangler, 1992). Moreover, our approach looks at attributions for previous events, which has been one of the areas where text coding has been applied in both organizational (Staw, McKechnie, & Puffer, 1983) and individual differences research (Burns & Seligman, 1989). One key advantage for machine learning approaches is that the unreliability of older approaches can be circumvented through a standardized and automatic method of coding. Machine learning allows us to identify words or phrases that signal some of the main reasons for leaving based on a priori categories, and learn from earlier iterations to better explain these reasons. For example, an applicant can write that s/he left the previous job because of excessive stress or poor working conditions. This means the person was seeking to avoid a bad job, although he/she did not explicitly use words like "leaving a bad job," or more abstract theoretical terms like "avoidance motive."

There is considerable heterogeneity among individuals when it comes to reasons to which they attribute previous turnover (T. W. Lee, Mitchell, Holtom, McDaniel, & Hill, 1999). Drawing on extant literature, we believe some of these reasons, especially if they repeat across several previous jobs, can send signals about relatively stable behavioral and attitudinal characteristics of the applicants. Therefore, although there are several different reasons for leaving previous jobs, such as continuing education, relocation, or incidents of caregiving, involuntary turnover, intrinsic reasons, etc., in developing our hypotheses, we only focus on the reasons that according to the literature can be interpreted as the signals of relatively stable behavioral and attitudinal characteristics, including, (1) involuntary, (2) avoiding bad jobs, and (3) approaching better jobs. Many studies have supported the consistency of job attitudes and work outcomes across jobs and organizations (e.g., Arvey, Bouchard, & Segal, 1989; Davis-Blake & Pfeffer, 1989; Newton & Keenan, 1991; Staw & Ross, 1985). Therefore, we expect that attributions or motives related to turnover to be indicative of a general orientation toward work that will show through in subsequent jobs.

To systematically find the main three reasons for leaving previous jobs in our data, we use supervised machine learning techniques in which we train a small sample of data (3% of the data) in that we take this small sample and manually categorize reasons for leavings into four categories, (1) involuntary, (2) avoiding bad jobs, (3) approaching better jobs, and (4) other reasons (see Table 1). The program learns about each category by finding the probabilities that different words and word combinations belong to each category. Then the program reads the remaining data which we call the test sample (97%

of the data) and finds the semantic patterns and themes in these texts provided by the applicants as reasons for leaving previous jobs using what it has learned from the co-occurring terms and phrases and their probability distributions over the four categories of reasons in the training sample. This process helps to identify key themes even if applicants may not fully divulge them if asked more directly.

In the next sections, we draw on the extant literature to discuss in detail why we focus on these three reasons for leaving in applicants' work history, and how these attributions of reasons for leaving can be predictive of future work outcomes.

History of involuntary turnover. Research and organizational practice have drawn a strong distinction between categories of voluntary and involuntary turnover, and as such, we believe this is important for us to incorporate them into our understanding of work history. Whereas voluntary turnover is the result of an employee's decision to terminate employment, involuntary turnover reflects a situation in which the organization makes the decision. As an example of our machine learning process, reasons related to involuntary turnover include "I was laid off due to a budget cut," "my position was eliminated because of budget cuts," or "my position was eliminated and I was excessed." Words and phrases associated with budget, cut, eliminate, position, and layoff are expected to co-occur in reasons that are related to involuntary turnover. The algorithm learns these words and phrases are related to one another in the training sample, and applies the rule on the rest of the data by searching for similar relationships among words in the test sample. The algorithm then categorizes each individual reason for leaving given by applicants into corresponding categories by calculating the probability distribution of that reason over the four categories of reasons. The algorithm repeats this process for all the reasons for leaving in the test sample and finds their probability distributions over the four reasons pre-defined in the training sample.

Several studies have found that employees who involuntarily leave their jobs tend to be lower performers compared to those leaving voluntarily (Barrick, Mount, & Strauss, 1994; Barrick & Zimmerman, 2009). In part, this relationship between involuntary turnover and performance is nearly tautological, since involuntary turnover is usually a function of poor performance or violation of organizational policies. Even in the case of layoffs, the selection of which individuals are terminated is often reflective of poor performance. Following the behavior consistency argument presented earlier, we hypothesize that applicants who note that they have lost jobs due to involuntary termination will demonstrate weaker performance in their future jobs. Davis, Trevor, and Feng (2015, p. 1) further note that individuals who have a history of being laid off tend to have more negative attitudes toward subsequent jobs, and in turn, are more likely to quite these subsequent jobs.

> ***Hypothesis 3:*** *Applicant attributions of previous turnover as involuntary, as assessed via supervised machine learning, is (a) negatively associated with teacher performance, and (b) positively associated with voluntary turnover hazard.*

History of avoiding bad jobs. There is an extensive research tradition that has differentiated individuals based on their long-term, dispositional motivational orientations. Scholars have come to find that key distinction is between an “avoidance” disposition and an “approach” disposition (Elliot & Thrash, 2010). Individuals with an avoidance disposition are marked by a tendency toward noticing negative or threatening features of the environment, experiencing anxiety when confronted with negative information, and behavioral attempts to avoid (rather than resolve) the resulting negative emotional stimuli. This “avoidance temperament” has been linked to many negative life and work outcomes (Diefendorff & Mehta, 2007; Elliot & Harackiewicz, 1996; Ferris et al., 2011). A focus on avoiding negative outcomes has been linked to attention to minimal standards of job performance, characterized by trying to find “minimally sufficient” levels of effort (Förster, Higgins, & Idson, 1998). While individuals with a strong avoidance focus may be able to complete core job tasks at a very basic level by showing up on time and completing strictly defined duties, feelings of engagement, and efforts to innovate, exert extra effort, or seek advancement in one’s career generally suffer (Elliot & Harackiewicz, 1996; Elliot & Sheldon, 1997). Finally, those motivated by avoidance are often so worried and distracted that they cannot perform well (Cury, Elliot, Da Fonseca, & Moller, 2006). Moreover, it is also possible that individuals who attribute previous quitting to problems with their former workplace are behaviorally prone to externalize blame for negative events. Such a pattern of external attributions and withdrawal are consistent with the concept of learned helplessness (Maier & Seligman, 2016). A pattern of externalizing blame and lacking motivation to change a situation is consistent with (low) core-self evaluations, as noted by Judge & Bono (2001), which is associated with poorer job performance.

We also believe that an avoidance focused attribution for job changes will be associated with higher probability of turnover. As a starting point, evidence clearly suggests that a disposition towards avoidance motivation is associated with lower levels of job satisfaction (Lanaj, Chang, & Johnson, 2012). The organizational literature widely supports the relatively strong link between job satisfaction and voluntary turnover (e.g., Chen, Ployhart, Thomas, Anderson, & Bliese, 2011; Griffeth et al., 2000; Schleicher, Hansen, & Fox, 2011; Trevor, 2001). Moreover, individuals who are avoidance focused will also be more prone to exit a job when problems arise, based on their generalized tendency to cope with problems by avoiding them.

Hypothesis 4: *Applicant attributions of previous turnover to avoiding bad jobs, as assessed via supervised machine learning, is (a) negatively associated with performance, and (b) positively associated with voluntary turnover hazard.*

History of approaching better jobs. There are several studies discussing that an approach motivational orientation toward desired outcomes is positively associated with positive work outcomes (e.g., Diefendorff & Mehta, 2007; Elliot & Harackiewicz, 1996; Ferris et al., 2011). The approach orientation can represent itself in seeking a better fit, following one’s passion, or looking for opportunities for advancement and development. Hom and Griffeth (1995) explained that employees usually have developed attitudes about the job for which they are applying before they start the job and those attitudes are predictive of work outcomes. Mowday, Porter, and Steers (1982) and Barrick et al. (1994) showed that the extent of applicant’s desire for the position for which s/he is applying is an important predictor of work outcomes. Wrzesniewski, Dutton, and Debebe

(2003) identified that interpreting one's work as a calling to be sought out is linked to more enjoyment, greater satisfaction and spending more time at work which all result in better performance and lower levels of turnover. Other studies found that a positive desire for one's work can positively contribute to long-term performance (Baum & Locke, 2004 e.g., Bonneville-Roussy & Lavigne, 2011; Vallerand, Mageau, Elliot, & Dumais, 2008). Other studies found that people who framed their work positively (e.g., as having positive effects on others) were more effective and more resilient in the wake of setbacks (Blatt & Ashford, 2006).

> ***Hypothesis 5:*** *Applicant attributions of previous turnover to approaching better jobs, as assessed via supervised machine learning, is (a) positively associated with performance, and (b) negatively associated with voluntary turnover hazard.*

2.3 Method

2.3.1 Data and Sample

We used data from 16,071 external applicants for teaching positions at the Minneapolis Public School District between 2007 and 2013. The district hired 2,225 of the applicants. Of these, 1,756 stayed with the district at least until the 2012-13 academic year, when the district introduced its teacher-effectiveness evaluation system, data from which will provide performance measures.

MPS is one of the largest school districts in Minnesota serving over 30,000 students each year and employing around 2,800 total teachers in recent years. Like most urban districts, it serves more diverse and disadvantaged students than the typical district.

About 70% of MPS students are students of color (state average 27%), 21% are English language learners (state average 7%), and 65% of students are eligible for free or reduced-price lunch (state average 39%).

To fill its hiring needs, the district publicly posts vacancy announcements. Typical positions needed would include elementary, high-school math, or special-education teacher. People apply for a position via the district's website using a series of web-forms that elicit semi-structured text similar to that commonly found on a resume. The central human-resources department does a light screening to ensure each applicant meets minimal qualifications, such as having required licenses. School-based hiring teams conduct interviews and make offers. According to the district, more than 90% of offers are accepted.

For each application, we have data on position and self-reported applicant characteristics. These included a detailed work history with job title, job description, reason for leaving, and start and end dates for each previous job. Some applicants also disclosed race and gender, although this was not required. For hires working in the 2012-2013 academic year or after, we were able to link application information to performance data. We have information on turnover for all participants who were hired.

2.3.2 Measures

Work experience relevance. A central challenge in automating resume screening is handling text data in a way that can leverage existing knowledge about occupations rather than relying on theory-free, text-mining approaches. We developed a technique to measure the relevance of work experience in a principled, easy, accurate way that leverages decades of accumulated knowledge embodied in the U.S. Department of Labor's Occupational Information Network (O*NET), a comprehensive database designed to describe occupations (Peterson, Mumford, Borman, Jeanneret, & Fleishman, 1999). We proceeded in 4 steps: (1) map past position job-title and job-description text to O*NET standard occupation code, (2) map occupation code to O*NET knowledge, skills, abilities and other characteristic (KSAO) space, (3) measure distance in KSAO space between the past and desired position, and, (4) to get a single applicant-specific measure, average this distance across all the applicant's past positions using a weighting function that favors more recent and longer-held positions.

For step (1), we used supervised machine learning techniques to develop an algorithm that automatically classified self-reported job titles and job descriptions into an O*NET standardized occupation code. Such classifiers were developed by learning the characteristics of different classes from a training sample of pre-classified documents (R. Feldman & Sanger, 2007; Mohri et al., 2012). We specifically used a Naïve Bayes Classifier, the most prevalent text classifier in machine learning (R. Feldman & Sanger, 2007; Mohri et al., 2012). Technical details are included at the end of the paper. We trained the classifier using the O*NET's detailed job descriptions and alternative job titles for each of 974 occupations as the training data (O*NET, n.d.). We made a "bag of words" for each O*NET standard occupation containing its description and commonly-reported job titles associated with the occupation. We then trained the classifier on these data to understand what word clusters predict what occupations.

Next, we ran the trained algorithm on the self-reported job description and job title as reported by each MPS applicant regarding a past position. The algorithm maps this to a standardized O*NET occupation. To validate the classification, we took a random sample from the self-reported previous jobs and hire a research assistant to classify the job descriptions into O*NET occupations. We compared the predicted occupation from the Naïve Bayes classifier with the RA's classification to calculate the agreement rate between human and machine classifications. They agreed in 92% of the cases in the sample.

In the second step, each past position's standard occupation was mapped to a point in KSAO space. O*NET provides detailed information about the required level and/or importance of different abilities, knowledge, skills, vocational interests, values, and styles for each occupation. This gave each occupation-*o* a profile, x_o, in a high-dimensional KSAO space.

Third, we operationalized work-experience relevance with a profile similarity index (PSI), measuring the similarity between an applicant's past occupation and the occupation sought. A PSI is a single value representing the extent to which a past occupation and the prospective one are (dis)similar across multiple variables (Converse et al., 2004; Edwards & Harrison, 1993). We specifically used *profile level* which measures dissimilarity and measures the extent to which scores in one profile tend to be higher or lower than scores within another profile. As is common, we used the L2 (Euclidean) distance between the two profiles (Converse et al., 2004; Edwards & Harrison, 1993).

Letting *a* index the past position and *b* index the desired position and letting *i* index the dimensions of KSAO space, the profile level measures dissimilarity as,

$$D_a = -\left(\sum_i (x_{ai} - x_{bi})^2\right)^{\frac{1}{2}}.$$

Distance measures dissimilarity. To measure relevance, distance was reverse coded.

Finally, to aggregate information across an applicant's entire work history, we computed a weighted average of *D* across all the applicant's past jobs. Applicants in our sample have an average of 3.18 previous jobs (SD=2.2). Several studies show that individuals often gravitate toward the jobs that match their KSAOs better (Converse et al., 2004; Wilk et al., 1995; Wilk & Sackett, 1996). Also, research shows that the tenure in the job impacts human capital accumulation (Gibbons & Waldman, 1999; Kuhn & Jung, 2016; Mincer & Polachek, 1978). As such, it is important to take into account the gap between the application year and the year when the applicant had each of the previous jobs as well as the length of tenure in each previous job. Therefore, we defined a weight for each previous job as the integral of the decay function of both the elapsed time since the person left the previous job (E_a) and their tenure in that job (T_a). The weight accorded to past position-*a* is,

$$w_a = \int_{E_a}^{E_a+T_a} e^{-x} dx$$

Our aggregate measure of an applicant's work-experience relevance is the w_a-weighted average D_a across the applicant's past positions. Across applicants, this was standardized.

Tenure history. We defined tenure history as the average deviation of applicant's tenure in prior jobs from the median tenure in each occupation category. Barrick and Zimmerman (2005) used average tenure in previous jobs as a signal for the tendency in applicants to leave. However, average tenure differs across occupation categories because of structural forces beyond the individual. Thus, it may not entirely reflect an individual's disposition to change jobs. To get a clearer measure of an applicant's disposition toward longer or shorter duration of employment relative to others in similar jobs, we collected median tenure in an applicant's relevant prior occupation category, reported on the department of labor's website ("United States Department of Labor, Bureau of Labor Statistics," n.d.). For each past position, we computed the difference between the applicant's tenure and relevant median tenure. Each applicant's tenure history is the average deviation across the applicant's prior positions.

Attributions for turnover history. We measured four variables from the self-reported attributions employees make for turnover history, including leaving (1) involuntarily, (2) to avoid bad jobs, (3) to seek better jobs, or (4) other reasons. We apply supervised machine learning to applicants' self-reported textual reasons for leaving each of their prior positions. We took a small sample of reasons for leaving from the data (1,000 out of 34,601 reasons). We manually categorized the reasons for leaving in the training sample into one of the above four reasons. Table 1 shows a sample of the training data. Using this training sample, we train the Naïve Bayes classifier to understand what word clusters predict what reasons. Next, we ran the trained algorithm on all the reasons for leaving in the test dataset to classify reasons for leaving previous jobs into the four pre-defined categories of attribution for turnover. The model provides a probability distribution of each self-reported reason for leaving over the four pre-defined categories. We compared the results of reasons classification for a random sample with human classifications done with an RA. The agreement between machine classification and human classification of the sample of reasons for leaving was 93%.

[TABLE 1]

Table 2 presents examples of reasons classified using supervised machine learning along with a probability distribution over attributions for turnover. It is worth noting that this model does not measure the extent to which or intensity with which one describes a particular factor associated with turnover, but rather, the probability that a given explanation fits into a category.

[TABLE 2]

Performance. In the 2012-2013 academic year, the district was one of the first in the nation to adopt a well-tested comprehensive system of multiple measures of performance to evaluate teaching performance (Kane, McCaffrey, Miller, & Staiger, 2013). These measures included the following:

Student evaluation. The district administered a survey to all students about their teachers twice each year starting in the 2013-2014 academic year. The questions asked students about the degree to which their teachers academically "engage", "illuminate", "manage", "relate", and "stretch" them and their peers. This survey is based on the Tripod Seven C's survey of teacher practice (Kane et al., 2013). Items and teachers are scored on a "favorability" metric. That is, items are scored 1 if a student responded "Yes" in grades

K-2 or "Mostly Yes" or "Yes, Always" in grades 3-12. Responses of "No" or "Sometimes" in grades K-2 or "No, Never", "Mostly No" or "Maybe/Sometimes" in grades 3-12 were scored 0. A teacher's score is simply the mean of their dichotomous item scores, multiplied by 100 resulting in a score between 0 and 100. Here are two examples of items used in the survey: “This class makes me a better thinker.” and “The teacher in this class really cares about me.”

Expert observations. Measures of effective instruction were scored after classroom observations four times each year by trained, certified raters against a rubric of effective instruction based on the widely-used Framework for Effective Teaching (Danielson, 2007). The raters evaluate teacher performance using a 20-item scale. All items used 4-point Likert-type scales with anchors of 1 (strongly disagree) to 4 (strongly agree). Examples of items included are, “Plans units and lessons effectively” and “Uses relevant resources and technology.”

Value-added. This measure of teacher performance was based on students’ standardized achievement tests in reading and/or math and student-teacher links based on teacher-verified rosters controlling for each student’s prior achievement level and other characteristics. This measure was only available for teachers who have taught math or reading since 2012. This measure was developed in an association between the school district and the Value-Added Research Center (VARC) at the University of Wisconsin (*Minneapolis value-added model.*, 2013). The model is based on a posttest-on-pretest regression, so the value-added scores represent a model of growth in student achievement over the course of a year of instruction. The model also includes controls for student characteristics and incorporates multiple pretests when available.

The district created a *z*-score for each teacher-year observed using the cross-sectional distribution of each measure among the district's teachers. Because our sample is new hires and there is a learning curve in teaching, the sample's average performance is below the district average. Each score also has a standard error, which depends on the reliability of the measure and the amount of information available for that teacher's measure, such as the number of a teacher's students responding to the surveys or taking the standardized tests. To aggregate information across measures, the district uses a composite measure of teacher performance computed with inverse-variance weighting. We used all of these four measures of performance (student evaluation, expert observations, value-added, and the composite) as dependent variables to compare and contrast the predictive validity of our predictors for various performance measures.

Our analysis is fundamentally cross-sectional because we are studying a one-time hiring decision. We constructed a measure incorporating information from many years of post-hire performance. To compare hires' performance on an equal footing despite their being observed during different spells of experience, we residualize each performance score (Z_{itm}) conditional on a simple, measure-specific, quadratic regression model of teacher-i's years since hire in year-t (X_{it}) using all observed teacher-years of performance for the measure-m. Then we score the residual for each observation: $Z_{itm} - E(Z_{itm}|X_{it}, X_{it}^2)$. For teacher-$i$ with $N_{im} > 0$ observations on performance measure-m, we measure performance as the average of residualized performance:

$$Y_{im} = N_{im}^{-1} \sum_{t=1}^{N_{im}} [Z_{itm} - E(Z_{itm}|X_{it}, X_{it}^2)]$$

Turnover. Among hires, we have access to the hire date and, if applicable, a turnover date and reason (voluntary or involuntary). Table 3 shows the voluntary and involuntary reasons for turnover according the district's HR department. We used survival analysis to calculate (voluntary or involuntary) turnover hazard, defined as the expected speed of turnover (Dickter, Roznowski, & Harrison, 1996). To measure turnover hazard, we also used employment duration in years. Turnover hazard allows us to measure whether and when the employee turned over (Dickter et al., 1996; Morita, Lee, & Mowday, 1993; Singer & Willett, 2003). When predicting voluntary (involuntary) turnover, the applicants who were terminated involuntarily (voluntarily) were treated as censored observations. A total of 349 individuals, or 16% of the sample of 2,225 applicants who were hired between 2007 and 2013 voluntarily turned over. The duration of employment for those who voluntarily turned over ranged from 1 to 9 years (Mean= 3.48 years, SD=1.68 years). A total of 398 individuals, or 18% of the sample of 2,225 hires involuntarily turned over. The duration of employment for them ranged from 1 to 9 years (Mean= 4.08 years, SD=1.85 years). Any employee who has not turned over by 2017 has an unknown eventual turnover date and are analyzed as right censored.

[TABLE 3]

Control variables. We wanted to get some proxy measure for applicant general writing skills that might be correlated with the quality of their application and job performance but which is not relevant to our core hypotheses. The qdap and hunspell packages in R are used to count spelling errors in each application, and serve as a potential index of these constructs. We reverse coded the resulting variable such that higher scores reflected fewer mistakes. We controlled for whether applicants have an advanced degree for similar reasons.

Several variables already used by the school district in selection were included because they serve as a baseline for comparison, and also because they may be related to our machine learning variables and performance, but are not relevant to our core hypotheses. We included whether applicants have worked as a teacher in the past since this may exert an influence on several performance ratings above and beyond the mere similarity of skills (e.g., teachers as raters may have ingroup biases toward those who have prior teaching experience). For similar reasons, we also controlled for whether they have been the district's employee before in any position. We also controlled for overall years of work experience, since this is potentially related to several of our central variables and performance. The average employment gap between their previous jobs was also included since it may be linked to employment history but is not central to our hypotheses.

Due to potential differences in ratings across jobs, we incorporated the type of teaching position they applied to (special education, science, math, reading, elementary school teacher, social science, and others) in our regressions so comparisons are made within applicants for the same type of position. To take into account the fact that everyone did not start working for the district at the same time, we control for application year.

Demographic variables. We do not control for race or gender because our purpose is to introduce a selection model independent of these variables. As such, the main results presented in our regression analyses do not incorporate them. However, we note that we also ran contrasting models that did include these demographic factors, and found that the results were nearly identical to those from our selection model, with no changes in the pattern of significance and only small changes in the magnitude of effects for our hypothesized predictors.

To evaluate the effectiveness of our proposed model in reducing the risk of adverse impact, we need the demographic variables to measure whether their predictive ability in determining selection changes under our proposed model. In our sample, 37% of applicants did not self-report their race and gender. Since we cannot determine whether the demographic values are missing for random reasons or because a specific group of people chose not to reveal their demographic characteristics, we cannot drop applicants who did not report their demographic information. For that purpose, using Minnesota statewide administrative data that includes name, gender and race for all teachers in the state, we build a reference database to train a supervised algorithm that classifies applicants with missing gender into female and male categories and classifies applicants with missing race into white and non-white categories. To validate the accuracy of our algorithm, we take a random sample of 100 hires who did not self-report their race and gender at application but did have demographic information in the district's administrative data. The race and gender retrieved from administrative data matched with the algorithm classification with 95% accuracy. Although we do not use race and gender in our predictive model, we later use these variables to evaluate whether our model reduces the risk of adverse impact.

2.3.3 Correction for Sample Selection Bias and Instrumental Variables

Because applicants went through a non-random selection process to be hired, estimates from an ordinary least squares regression of work outcomes on predictors *among hires only* might produce estimates suffering from omitted-variable bias and range restriction (Sackett & Yang, 2000). To correct for this, we use a Heckman selection correction (Heckman, 1979). As instrumental variables, we use the quality and quantity of the competition an applicant faced in applying for the position, both of which will affect an applicant's chance of being hired, but are uncorrelated with unobserved applicant characteristics. In other words, these instruments shift an applicant's probability of hire, but do not affect post-hire performance or turnover. Similar variables have been used as instruments before in the context of teacher selection (Goldhaber, Grout, & Huntington-klein, 2014).

To measure the quantity of an applicant's competition, we calculated the share of applicants hired for the position. To measure the quality of the competition, we ran a Probit model using all predictors and control variables from the applicant pool to predict the likelihood of being hired. For each applicant, this yields a predicted probability of hire. To measure the quality of an applicant's competition, we use the average predicted hire probability of their competitors for the position.

2.3.4 Evaluating the Effectiveness of our Proposed Selection Model

We evaluate the effectiveness of our proposed models in terms of (1) lowering the risk of adverse impact and (2) helping to select higher performers or longer-serving hires. To do so, we developed a list of model-recommended hires based on hiring applicants with the best predicted post-hire outcome. We recommend the same number of applicants as the district hired each year in each position type. For example, if the district hired 100 of 300 applicants in 2013 for the position of special-education teacher, we recommend the 100 applicants who applied to that position in that year who, according to our model, are predicted to have the highest levels of performance.

Adverse impact. We compare the power of the demographic variables to predict hiring under the observed selection system and recommended hiring under our model using two simple Probit models. If our model lowers the risk of adverse impact relative to the district's real hiring decisions during the period studied, the demographic variables will have less explanatory power for our recommendations than for the observed hiring decisions. Results are reported in Table 9. In the first model, the outcome is whether the applicant actually was hired and in the other models it is whether the applicant is recommended for hire by each of our models. Predictors include gender and race dummy variables, age and age-squared, and control variables for application year and position type.

Model effectiveness comparison. To evaluate the effectiveness of our proposed selection model in terms of selecting high performers against the observed selection system, we use three approaches. First, we score all applicants' predicted performance and compare average predicted performance between actual hires and model-recommended hires. However, because we recommend on the basis of this predicted performance, this difference may overstate the improvement the model could generate. A second way that accounts for uncertainty in the prediction and grounds prediction back in actual performance follow these steps:

(1) break hires into deciles of actual performance and deciles of predicted performance.

(2) build a 10×10 confusion matrix (Table 10) showing the probability distribution of actual decile conditional on each predicted decile. For instance, the bottom row expresses the shares of those in decile 10 of predicted performance who are observed in deciles 1 through 10 of actual performance.

(3) Calculate the expected actual decile for each predicted decile.

(4) Predict performance for each applicant. Use the predicted-performance deciles' ranges among hires from (1) to assign each applicant a predicted-performance decile. Then assign each an expected actual-performance decile using (3).

(5) Compare expected actual decile between actual hires and model-recommended hires.

Third, among hires, compare actual performance between two groups: those where the model-recommendation agrees with the district decision to hire and those where the model disagrees. The agree group having higher, observed performance than the disagree group would provide evidence consistent with the model adding value.

2.4 Results

Table 4 and 5 present the intercorrelations and the descriptive statistics for the study variables. Except for the factor variables, all independent variables are standardized. The numbers reported in table 5 are variable summaries before being standardized.

[TABLE 4]

[TABLE 5]

To predict each of the four measures of performance, we estimated a Heckman regression using Stata 14 using Maximum Likelihood specification. This is preferred over OLS analysis in the hired-only subsample due to the threat of omitted-variable or selection bias created by the fact that outcomes are observed only for those who are hired (Clougherty, Duso, & Muck, 2016; Wooldridge, 2010). If unobserved determinants of performance are correlated with predictors of hire, estimates from OLS will be biased. Our approach corrects for this by harnessing instrumental variables that shift each individual's probability of hire but are not related to unobservable determinants of her performance. Table 6 compares the first stage of Heckman model to a similar probit model excluding the instruments. The first column reports estimated effects of different predictors on the probability of getting hired from a probit. The second column adds the instruments we have defined, the quality and quantity of competition faced by each job applicant. These are strong predictors of the probability of getting hired but should not be related to unobserved determinants of individual performance or turnover conditional on hire.

[TABLE 6]

Table 7 shows the estimated outcome models, the Heckman second stages, with columns varying only the post-hire outcome. They show that work experience relevance (H1a) is positively associated with expert observations, value-added, and the performance composite ($\beta_{\text{work experience relevance - Expert observation}}=0.05$, $p<0.01$; $\beta_{\text{work experience relevance -Value-Added}}=0.11$, $p<0.01$; $\beta_{\text{work experience relevance -Performance composite}}=0.05$, $p<0.01$), but not with the student evaluation of teacher performance. In support of Hypothesis 2a, tenure history has a significant positive effect on expert observations, value added, and the performance composite ($\beta_{\text{Tenure history-Expert observation}}=0.08$, $p<0.01$; $\beta_{\text{Tenure history -Value-Added}}=0.08$, $p<0.05$; $\beta_{\text{Tenure history-Performance composite}}=0.07$, $p<0.05$). Again, there is no evidence supporting that tenure history has any impact on the students' evaluation of teacher performance. Leaving previous jobs due to involuntary turnover (H3a) only predicts expert observations and performance composite ($\beta_{\text{Involuntary turnover-Expert observation}}=-0.06$, $p<0.05$; $\beta_{\text{Involuntary turnover-Performance composite}}=-0.07$, $p<0.01$). Leaving to avoid a bad job (H4a) is negatively related to student evaluations, expert observations, value added, and the performance composite ($\beta_{\text{Avoid bad-Student evaluation}}=-0.14$, $p<0.01$; $\beta_{\text{Avoid bad-Expert observation}}=-0.17$, $p<0.001$; $\beta_{\text{Avoid bad -Value-Added}}=-0.11$, $p<0.001$; $\beta_{\text{Avoid bad -Performance composite}}=-0.18$, $p<0.01$). Finally, leaving to seek a better job (H5a) is positively associated with all the performance measures ($\beta_{\text{Seek better-Student evaluation}}=0.09$, $p<0.05$; $\beta_{\text{Seek better-Expert observation}}=0.09$, $p<0.01$; $\beta_{\text{Seek better -Value-Added}}=0.09$, $p<0.01$; $\beta_{\text{Seek better-Performance composite}}=0.09$, $p<0.01$). A negative coefficient on the Inverse Mills Ratio (IMR), as in the models for expert observation and the performance composite ($\beta_{\text{IMR-Expert observation}}=-0.10$, $p<0.05$;

$\beta_{\text{IMR-Performance composite}}=-0.09$, $p<0.001$), gives evidence that unobservable factors which increase hiring probability tend to push down these outcomes.

[TABLE 7]

To estimate the hazard function for voluntary and involuntary turnover, we use the Cox partial likelihood method (Morita et al., 1993; Singer & Willett, 2003). We also corrected for selection bias in these models by including the inverse Mills ratio from the Heckman model as a proxy for unobservable determinants of hire. Table 8 reports the results. The hazard function of the Cox model is given by r(t, x) =h(t) $e^{\beta x}$, where h(t) is the baseline hazard, x is a vector of covariates, and β is a vector of regression coefficients. The Cox method is a semi-parametric approach not requiring any assumption about the distribution of the hazard function. However, the hazard functions should be proportional for different covariates, so that the effects of the covariates on the criterion does not change over time (Cleves, Gould, Gutierrez, & Marchenko, 2016). To test this assumption, we run the Grambsch and Therneau (1994) maximum likelihood test. We failed to reject the null hypothesis (*p=0.14*) that the log hazard-ratio function is constant over time, which suggests our model did not violate the assumption required for Cox model.

Results presented in table 8 show that one standard deviation increase in work experience relevance (H1b) is predicted to decrease voluntary turnover hazard by 8% ($H_{\text{Work experience relevance-Voluntary turnover}}=0.92$, $p<0.001$), whereas the same change in the tenure history (H2b) is predicted to decrease voluntary turnover hazard by 11% ($H_{\text{Tenure history-Voluntary turnover}}=0.89$, $p<0.05$). We found an opposite relationship as we hypothesized

(H3b) between leaving previous jobs due to involuntary turnover and hazard of voluntary turnover, showing a negative link between leaving due to involuntary turnover and the hazard of voluntary turnover ($H_{\text{Involuntary turnover-Voluntary turnover}}$ =0.87, p<0.01). We do not find any support for hypothesis 4b that there is a positive relationship between leaving prior positions to avoid bad jobs and the hazard of voluntary turnover. Finally, we do not find any support for hypothesis 5b that there is a negative relationship between approaching a better job and the hazard of voluntary turnover. The results for the hazards of involuntary turnover and overall turnover are also reported in table 8. The results support a negative relationship between tenure history and the hazard of involuntary turnover, so that one standard deviation increase in tenure history is linked to 13% decrease in the hazard of involuntary turnover($H_{\text{Tenure history-Involuntary turnover}}$ =0.87, p<0.05). Our results show a positive relationship between avoiding a bad job and the hazard of involuntary turnover, so that one standard deviation increase in avoiding a bad job is associated with 10% increase in the hazard of involuntary turnover ($H_{\text{Avoid bad-Involuntary turnover}}$ =1.10, p<0.001). We do not find any support for a relationship between our other predictors and the risk of involuntary turnover. The relationship between the predictors and overall turnover are very similar to those for voluntary turnover, but weaker.

[TABLE 8]

2.4.1 Evaluating the Effectiveness of our Proposed Model

As shown in the last column of Table 9, gender, race, and age are each strong predictors of hire in the district's actual selection system (β_{female} = 0.06, p<0.05; β_{white} = 0.11, p<0.01; β_{age} = 0.48, p<0.001; β_{age^2} = -0.13, p<0.001). However, across our models of all post-hire outcomes, following the model's recommendation would imply selection decisions where gender and race are not significant predictors of hire. For example, selecting on predicted composite performance yields no association of hiring with gender or race ($\beta_{female} =$ -0.02, n.s.; $\beta_{white} =$ 0.02, n.s.). Similar results are obtained across all models. Age is still a predictor of selection in our models but its effect size is smaller than that in the district's observed selection model, (e.g., selecting on composite performance model we have: $\beta_{age} =$ 0.35, p<0.001; $\beta_{age^2} =$ -0.13, p<0.001).

Table 10 shows the confusion matrix comparing actual and predicted deciles of performance composite across hires. For instance, among those hires predicted to be in the 10th decile of performance, 24% were observed in the 10th decile of actual performance but 73% were in the top 5 deciles. Using this table, we calculated the expected actual decile for each predicted decile among hires, which is displayed in the last column. For the 10th decile of predicted performance, the expected actual decile is 7.03, which is 0.79 deciles above that of the 9th decile.

Table 11 reports results from our first two evaluations of model performance. Independent samples *t*-tests were used to compare mean predicted composite performance scores of actual hires versus model-recommended hires and to compare their mean expected actual performance deciles. Under both measures, model-recommended hires ($M_{\text{performance composite scores}}$ = 0.37; $M_{\text{expected actual performance decile}}$ =6.26) are predicted to be more effective than actual hires ($M_{\text{performance composite scores}}$ = 0.11; $M_{\text{expected actual performance decile}}$ =5.54). As shown in Table 11, both *t*-test evaluations show a significant and large predicted performance difference between the two groups.

Finally, among hires, we compare the average actual performance of those who our model would recommend versus those who our model would not recommend. The result shows that the average performance composite of the recommended group ($M = 0.33$) is significantly higher than that of the not-recommended group ($M = -.11$) (difference=0.43, p-value<0.001). If the model were just picking up noise, the two groups would be the same in expectation. Instead, the model is successfully sorting hires into groups that differ significantly and substantially in observed performance. In terms of other outcomes, selecting to maximize predicted composite performance this way also generates a positive difference between the recommended and not recommends groups on student evaluations (difference = 0.11, p-value<0.10), expert evaluation (difference=0.43, p-value<0.001), and value added (difference = 0.22, p-value<0.001) but does not create a significant difference in expected years of retention (difference = 0.06, p-value >0.10). The top row of Table 12 communicates these results. The following four rows repeat this exercise but, instead of making recommendations to maximize predicted composite performance, recommendations are made to maximize predicted student evaluations, predicted expert evaluations, predicted value added, and predicted years of retention, respectively, and results describe how these induced recommendations affect the difference in each outcome. None of the decision rules induce significant, negative effects on other outcomes.

2.5 Discussion

The need for tools that facilitate the rapid collection and analysis of application information is constantly growing, and organizations struggle to find the best ways to be competitive in this environment. Responses have varied considerably. On one extreme, human resource practitioners have taken to very rapidly scanning through a large number of applications by keywords, relying on either a very small number of cues or heuristics for rejecting candidates. Alternatively, completely ad hoc methods for using large datasets have been employed, well-calibrated to a specific applicant pool and selection moment, but yielding prediction models that are unlikely to generalize to future occasions and poorly integrated with the substantial body of knowledge already present in the field of selection. The method evaluated in this study proposes a middle way, that combines machine learning techniques that are directed to find and analyze themes that correspond to established selection techniques. Through this process, we are able to score applicant quality using relevant work experiences, tenure history, and reasons for leaving previous jobs.

2.5.1 Conceptual implications

The conceptualization of work experience relevance developed through machine learning focuses on specific job tasks across different occupations rather than job titles by themselves. There is no question that the predictive power of work experience is maximized by using task details (Dokko et al., 2009; Tesluk & Jacobs, 1998). By pairing job titles with job analyst ratings of task requirements, we are able to use verifiable information, rather than relying on the unique words applicants use to describe previous job tasks in a résumé. The machine learning system also makes it possible to predict the likelihood of one having used KSAOs in a more refined and continuous manner than alternative methods of matching titles across fields. Moreover, while previous work has mostly used this information on experience for the prediction of job performance, ours is the first study of which we are aware that has used task-specific job experiences to also predict voluntary turnover. The link between relevant work experience and turnover suggests that theories of person-job match in the turnover and job attitudes literature can be integrated more fully with other work on job performance.

The results related to tenure history and turnover are largely in line with prior work related to the “hobo syndrome” (Judge & Watanabe, 1995; Munasinghe & Sigman, 2004). While this finding has been shown previously, we also found that tenure history can be linked to performance on the job. The reason for these linkages is not entirely clear based on our data, but it does raise some intriguing questions that might be examined in the future. One possibility is that individuals who switch jobs often have short time horizons for their work and, therefore, have less motivation to become proficient (Rusbult & Farrell, 1983). In a sense, this is a rational response, mirroring models of organizational commitment that show investment of time and energy into an organization are proportional to the expected duration of the relationship. On the other hand, it may be the case that individuals with a history of short tenure are not very good employees for reasons not measured in our study or other prior research, and their poor performance fuels leaving jobs quickly in a somewhat futile search to find a better fit.

We found that those who left a previous job to avoid a bad job were worse performers and were more likely to turnover. This does mirror our expectations based on the demonstrated consistency of negative job attitudes across employers. We go somewhat further than this evidence of job attitude stability though, since we show these stable tendencies can be related to downstream measures of performance and turnover in future jobs. This finding also may shed light on the attitude-performance relationship that has been so difficult to examine because of the reciprocal influence of these variables. In our study, the employment attitude data are collected prior to performance can even exist, and therefore the direction of the relationship is much easier to evaluate.

Leaving prior jobs to seek a better job also extends the literature on job attitude carryover by showing that motivation may carry over from the job search process to employment as well. Individuals who leave a job because they wish to do something more personally meaningful are shown to be superior workers.

2.5.2 Practical Implications

Organizations more than ever have access to large amount of text data from job applicants including applicants' responses to the online application forms, their cover letters, and their resumes. Our study helps organizations utilize these data to improve work outcomes while lowering the risk of adverse impact. Also, our method can help job applicants and organizations alike by making the selection process more objective through reducing the likelihood of recruiters' biases or applicants' influence tactics to deviate the selection process.

Relevant experience has many positive features in practice beyond verifiability. In particular, work experience is seen as highly relevant and acceptable for selection purposes by organizational leaders and job applicants (Hausknecht, Day, & Thomas, 2004). One key standard for legal defensibility is the use of job analysis information in the selection procedure (Borden & Sharf, 2007)—using O*Net job characteristics linked to prior work history is perfectly matched to this legal requirement. There are also concerns regarding personality or integrity tests because most applicants have some sense of how to “fake good” on such measures (Birkeland, Manson, Kisamore, Brannick, & Smith, 2006), and many applicants and organizations believe these questions are not job relevant (Hausknecht et al., 2004). Experience measures are less prone to this type of faking. Several studies show that the likelihood of applicants engaging in dishonest impression management tactics in the verifiable and more objective parts of their application form such as education or work history is considerably lower compared to that in other parts of job application such as in cover letters or during the job interview (Brown & Campion, 1994; Cole et al., 2007; Knouse, 1994; Ployhart, 2012; Waung et al., 2016).

In the area of education, our study can improve the teacher selection process by predicting the performance and turnover of potential teachers using data from their pre-hire application forms. It is crucial for several different reasons. First, the existing literature supports that improving the teacher selection process to hire effective teachers who are willing to stay with the schools, especially in public schools, can help improve the quality of education, which leads to narrowing the achievement gap (e.g., Aaronson, Barrow, & Sander, 2007; Adnot, Dee, Katz, & Wyckoff, 2016; Chetty, Friedman, & Rockoff, 2014; Hanushek, Kain, O’Brien, & Rivkin, 2005; Jackson, 2012). Second, research shows that schools spend about 80 percent of their budget on labor. However, their hiring practices are ineffective and inconsistent. Schools hire essentially at random (Goldhaber et al., 2014), wait up to three years to act on the measures of effectiveness, and decide whether or not to dismiss ineffective teachers. This performance-based process subjects many children to years of ineffective teaching, as well as wasting parts of the budget on frequent hiring and firing. Improved selection might reduce our need to learn about teacher performance on the backs of children (Staiger & Rockoff, 2010). Third, most teachers in public schools are unionized, and decisions about their compensation, job design, or termination are mandatory subjects of collective bargaining. However, management has greater flexibility to innovate in the selection of potential employees than other HRM areas. Factors like work history are legally acceptable predictors of work outcomes, since work history is explicitly considered as a legitimate job-related criterion by the Equal Employment Opportunity Commission (1978, Section 14, B.3) (Barrick & Zimmerman, 2005). Finally, improving the quality of teacher selection has a substantial impact on nation's economy, welfare, and human capital. According to the Bureau of Labor Statistics, about 4 million teachers were engaged in classroom instruction in 2016. This number accounts for 3% of the US workforce. Teachers also contribute to the quality of human capital by educating the future workforce. Evidence suggests that teaching that exceeds mean performance by one standard deviation increases students' success in adult life and produces, conservatively, over $200,000 in net present social value for each teacher per year (Chetty et al., 2014; Hanushek, 2011).

2.5.3 Limitations and Future Directions

Our study has several limitations. We do not have the actual demographic data for 37% of our sample. So, we had to impute the missing values using machine learning techniques. It increases the risk of error in assessing the risk of adverse impact. Second, this study only includes one public school district in the U.S. It would be helpful to expand this study beyond one district and examine the predictive ability of the variables we introduced here in other settings. Although our study may be generalizable to other workers such as nurses, doctors, social workers or other service jobs similar to teachers for which aspects like approach motivation, interest or specific individual characteristics are important, it would be informative to examine the predictive validity of the proposed variables in this study in jobs of different nature too. Third, in this study we only show the direct relationships between the predictors and outcomes. Future studies can investigate different mechanisms that connect these predictors to work outcomes. For example, we show that those who expressed that they left a previous job to seek a better job are more likely to high performers and stay longer with these organizations. Further study is needed to explain why this relationship exists.

2.6 Technical Details

2.6.1 Naïve Bayes Classification

In this document classification method, we first convert each document (self-reported job description) to a feature vector, **d** = (*w*1, *w*2, . . .), so that each meaningful word is represented in a column by the number of times each word occurs in the document. This representation is called the "*bag of words*" representation in which the order of the words is not represented (R. Feldman & Sanger, 2007). For instance, assume we have the following two documents in our data, reflecting part of an applicant's job responsibilities:

1- work with schools to improve their diversity practices.

2- developed a diversity initiative in the district.

The document-term matrix that represents these documents would be as below. The rows reflect each of the two documents.

$$\begin{array}{ccccccccc} \text{W} & \text{s} & \text{i} & \text{th} & \text{di} & \text{p} & \text{d} & \text{in} & \text{di} \\ \end{array}$$
$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 \end{bmatrix}$$

Note that the algorithm ignores the common words, or "stop words," such as "to", "the", or "with."

In the Naïve Bayes approach, we define the probability that the document *d* belongs to class *c* using Bayes theorem as follows:

$$P(c|d) = \frac{P(d|c)P(c)}{P(d)}$$

We need to choose a priori bag of words that gives information regarding each class based on what we have in the training set (Manning & Schütze, 1999). In this study, we use O*NET standardized job descriptions and job titles as the training set in classifying self-reported job title and descriptions into O*NET standardized occupations. We use a manually trained data set for the reasons for leaving classification.

The marginal probability *P*(*d*) is constant for all classes and can be dropped. The assumption of Naïve Bayes method to calculate *P*(*d*|*c*) is that all features in the document vector **d** = (w_1, w_2, ...,w_n) are independent:

$$\mathrm{P(d|c)} = \prod_i P(w_i|c)$$

So, the classifier function would be:

$$P(c_i|d) = \prod_i P(w_i|c_i)\, P(c_i)$$

Using the a priori class information in the training set, the *Bayes' classifier* chooses the class with the highest posterior probability; that is, it assigns class C_m *to* a document if

$$\mathrm{P}(\mathrm{C_m}|\mathbf{d}) = \max_i P(c_i|\boldsymbol{d})$$

2.7 Tables

Table 2-1 Sample of the Training Dataset

Attributions for turnover	Reasons for leaving
Involuntary	low student enrollment budget hold back from state
Involuntary	school closed due to low enrollment
Involuntary	reorganization after turnaround transferred management back to Dutch owners
Involuntary	company went under due to economic situation
Involuntary	position eliminated due to recession
Avoid a bad job	the school wasn’t a good fit for my teaching style
Avoid a bad job	I was unhappy and I resigned my position
Avoid a bad job	I was pretty much burntout
Avoid a bad job	air pollution no health insurance low pay
Avoid a bad job	bad management not enough hours
Approaching a better job	interested in having a more challenging position
Approaching a better job	I’m interested in education and am now pursuing my dream
Approaching a better job	I love working with kids my passion is in teaching and promoting learning
Approaching a better job	a new professional challenge and an opportunity for professional growth
Approaching a better job	advancement in career opportunity to grow personally and professionally
Other	birth of my daughter
Other	I had a baby
Other	relocated for family illness
Other	husbands job was transferring
Other	began master of education program

Table 2-2 Table A Sample of Classifying Reasons for Leaving into Four Categories of Attributions for Turnover Using Supervised Machine Learning

Reasons for leaving: Representative statements	Probability distribution over attributions for turnover			
	Approach better job	Avoid bad job	Involuntary turnover	Other reasons
Interested in expanding my professional career in a diverse setting where my skills and commitment to education will serve the students, parents and district	1	0	0	0
I miss working with students face-to-face and would like to work in an urban setting	1	0	0	0
Was not satisfied with the high caseload and hours; on-call work	0	1	0	0
Dissatisfied with pay same as subbing and environment	0	1	0	0
Position was eliminated at the end of the school term due to budget cuts	0	0	1	0
My contract was not renewed	0	0	1	0
I am looking to return to public school employment the atmosphere and professional climate at a private parochial school does not fit with my views and philosophies of education	0.47	.53	0	0
I moved on to a new employment opportunity at [name of the school] where I could learn more about serving clients with disabilities. [name of the school] did not provide this learning opportunity.	0.67	0.33	0	0
This is a one academic year position that is grant funded. I have a desire to return to the classroom as a teacher	0.82	0	0.18	0
The district did not renew my contract for the school year. I am interested in working with students in a diverse setting that is both challenging and rewarding	0.86	0	0.14	0
Not tenured after three years at XXX. Different supervisors during probationary period. Unclear how to meet expectations	0	0.29	0.71	0
Evaluation team was dissolved and the job duties changed	0	0.46	0.54	0
I was graduating from college and moving to a new location to begin graduate school	0	0	0	1
Sought employment closer to home after birth of child	0	0	0	1

Table 2-3 District's Voluntary and Involuntary Turnover Categories

Voluntary turnover	Involuntary turnover
Health Reason	Discharged
Not Eligible Extend LOA	Probationary Release-Performance
Personal Reasons	Resigned in lieu of termination
Educator in Another District	Discontinuance of Contract
Educator in Another State	End Temp Assignment
	Inactive
	Lay Off
	License/Certification Require
	Probationary Release-Staff Reduction

Table 2-4 Intercorrelations for the Study Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Outcome Variables															
1.Student evaluation	1.00														
2.Expert observation	0.35	1.00													
3.Value-added	0.13	0.25	1.00												
4.Performance composite	0.35	0.96	0.34	1.00											
5.Voluntary turnover	-0.10	-0.13	-0.05	-0.16	1.00										
6.Involuntary turnover	-0.09	-0.17	-0.04	-0.18	-0.20	1.00									
7.Work experience relevance	-0.05	0.05	0.06	0.05	-0.10	0.02	1.00								
8.Tenure history	-0.02	0.11	0.08	0.15	-0.12	0.02	0.09	1.00							
History of leaving previous jobs															
9.Involuntary turnover	-0.00	-0.03	-0.01	-0.03	-0.06	-0.03	0.10	-0.08	1.00						
10.Avoiding bad jobs	-0.14	-0.22	-0.13	-0.22	0.03	0.12	-0.01	0.00	-0.09	1.00					
11.Approaching better jobs	0.13	0.13	0.10	0.15	-0.11	-0.01	0.04	0.10	-0.24	-0.13	1.00				
Instruments															
12.Competition-Quantity	0.01	-0.05	0.02	-0.07	0.11	-0.03	-0.14	-0.41	-0.09	-0.01	-0.05	1.00			
13.Competition-Quality	-0.03	0.06	-0.03	0.06	-0.07	0.02	0.08	0.32	0.03	-0.04	0.07	-0.59	1.00		
Control variables															
14.Spelling accuracy	0.07	0.03	0.03	0.04	0.00	-0.03	-0.02	0.11	-0.09	-0.07	0.01	0.06	-0.00	1.00	
15.Years of experience	-0.03	0.03	0.04	0.07	-0.14	0.08	0.13	0.61	0.03	0.01	0.06	-0.41	0.26	-0.19	1.00

Note. Values greater than or equal to 0.07 are significant at $p<0.05$.

Table 2-5 Descriptive Statistics for the Study Variables

Variable	N	Mean	SD
Outcome Variables			
Performance composite	1756	-0.17	0.75
Expert observation	1728	2.92	0.25
Student evaluation	1342	82.71	6.14
Value-Added	866	2.98	0.63
Voluntary turnover	2225	0.16	0.36
Involuntary turnover	2225	0.18	0.38
Work experience relevance	16071	16.07	4.93
Tenure history	16071	-1.66	4.5
History of leaving previous jobs			
Involuntary turnover	16071	0.15	0.23
Avoiding bad jobs	16071	0.13	0.19
Approaching better jobs	16071	0.20	0.26
Instruments			
Competition-Quantity	16071	0.84	0.13
Competition-Quality	16071	0.14	0.08
Control variables			
Spelling accuracy	16071	0.74	1.42
Years of experience	16071	7.8	7.08
Prior district employment	16071	0.23	0.42
Prior work as a teacher	16071	0.17	0.38
Advanced degree	16071	0.47	0.49
Employment gap	16071	0.44	0.82
Demographic variables			
Female	16071	0.76	0.42
White	16071	0.84	0.37
Age	16071	33.12	10.62

Table 2-6 Heckman First Stage

Variable	Hired	Hired
Work experience relevance	0.12^{***}	0.09^{***}
	(0.03)	(0.02)
Tenure history	0.08^{***}	0.05
	(0.03)	(0.03)
History of leaving previous jobs		
Involuntary turnover	-0.01	-0.02
	(0.01)	(0.01)
Avoiding bad jobs	-0.02^{**}	-0.02^{*}
	(0.01)	(0.01)
Approaching better jobs	0.05^{***}	0.03^{***}
	(0.01)	(0.01)
Control variables		
Spelling accuracy	0.04^{***}	0.03^{**}
	(0.01)	(0.01)
Years of experience	0.02	-0.02
	(0.01)	(0.01)
Prior district employment	0.99^{***}	0.83^{***}
	(0.06)	(0.04)
Prior work as a teacher	0.44^{***}	0.44^{***}
	(0.04)	(0.04)
Advanced degree	0.09^{**}	0.02
	(0.03)	(0.03)
Employment gap	-0.02	-0.01
	(0.02)	(0.02)
Instruments		
Competition-Quantity		-0.45^{***}
		(0.02)
Competition-Quality		-0.07^{***}
		(0.02)
Controlled for application year and position type	Yes	Yes
R-Squared	0.19	0.26
Observations	16071	16071

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, Standard Errors adjusted for 7 clusters in application years.

Table 2-7 Models Predicting Different Measures of Teacher Performance- Heckman Second Stage

Variable	Student evaluation	Expert observation	Value-Added	Performance composite
Work experience relevance	-0.04	0.05**	0.11**	0.05**
	(0.04)	(0.02)	(0.03)	(0.02)
Tenure history	-0.00	0.08**	0.08*	0.07*
	(0.05)	(0.03)	(0.03)	(0.03)
History of leaving previous jobs				
Involuntary turnover	0.01	-0.06*	0.00	-0.07**
	(0.02)	(0.03)	(0.01)	(0.03)
Avoiding bad jobs	-0.14**	-0.17***	-0.11***	-0.18**
	(0.06)	(0.02)	(0.02)	(0.02)
Approaching better jobs	0.09*	0.09**	0.09**	0.09**
	(0.04)	(0.03)	(0.03)	(0.04)
Inverse Mills Ratio	-0.11	-0.10*	0.23	-0.09***
	(0.09)	(0.04)	(0.13)	(0.04)
Control variables				
Spelling accuracy	0.04***	0.01	0.03	0.02
	(0.01)	(0.01)	(0.03)	(0.01)
Years of experience	-0.08*	-0.09*	0.02	-0.06
	(0.03)	(0.04)	(0.02)	(0.03)
Prior district employment	-0.19*	-0.06	0.07	-0.01
	(0.08)	(0.16)	(0.12)	(0.18)
Prior work as a teacher	0.05	0.07***	0.07	0.07***
	(0.05)	(0.02)	(0.04)	(0.02)
Advanced degree	0.02	0.18***	-0.02	0.19***
	(0.02)	(0.05)	(0.04)	(0.05)
Employment gap	0.01	0.01	0.02**	0.01
	(0.01)	(0.02)	(0.01)	(0.02)
Controlled for application year and position type	Yes	Yes	Yes	Yes
Observations	1,342	1,728	866	1,756

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard Errors adjusted for 7 clusters in application years.

The numbers of observations are different across models because different performance evaluations started at different times, and were used for different position types.

Table 2-8 Survival Models Predicting Voluntary & Involuntary Turnover

Variable	Voluntary Turnover	Involuntary Turnover	All Turnover
Work experience relevance	0.92***	0.96	0.94*
	(0.02)	(0.04)	(0.03)
Tenure history	0.89*	0.87*	0.88*
	(0.05)	(0.07)	(0.05)
History of leaving previous jobs			
Involuntary turnover	0.87**	1.03	0.95
	(0.05)	(0.03)	(0.03)
Avoiding bad jobs	1.02	1.10***	1.06***
	(0.03)	(0.02)	(0.02)
Approaching better jobs	0.94	1.00	0.97
	(0.04)	(0.03)	(0.03)
Inverse Mills Ratio	0.93	0.92	0.92
	(0.09)	(0.07)	(0.05)
Control variables			
Spelling accuracy	1.01	1.05	1.03
	(0.01)	(0.05)	(0.03)
Years of experience	0.95	1.13***	1.05
	(0.07)	(0.03)	(0.04)
Prior district employment	0.71***	1.01	0.89**
	(0.05)	(0.09)	(0.03)
Prior work as a teacher	0.78**	0.88	0.83***
	(0.06)	(0.07)	(0.03)
Advanced degree	0.97	1.23***	1.10***
	(0.06)	(0.04)	(0.03)
Employment gap	1.03	0.93*	0.98
	(0.03)	(0.03)	(0.01)
Controlled for application year and position type	Yes	Yes	Yes
Observations	2225	2225	2225

Note. Standard errors in parentheses, * p<0.05, ** p<0.01, *** p<0.001. Standard Errors adjusted for 7 clusters in application years.

Table 2-9 Probit Models Comparing the Change in the Risk of Adverse Impact

	Recommended Based on Performance composite	Recommended Based on Student evaluation	Recommended Based on Expert observation	Recommended Based on Value-added	Recommended Based on Turnover	Actual Hires
Female	-0.02 (0.03)	-0.00 (0.03)	-0.01 (0.03)	-0.01 (0.03)	-0.01 (0.03)	0.06* (0.03)
White	0.02 (0.04)	0.02 (0.04)	-0.01 (0.03)	0.01 (0.04)	-0.09* (0.04)	0.11** (0.04)
Age	0.35*** (0.02)	-0.10*** (0.02)	0.26*** (0.02)	0.58*** (0.02)	0.59*** (0.02)	0.48*** (0.02)
Age^2	-0.13*** (0.01)	-0.05*** (0.01)	-0.11*** (0.01)	-0.15*** (0.01)	-0.08*** (0.01)	-0.13*** (0.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.82*** (0.09)	-0.96*** (0.09)	-0.83*** (0.09)	-0.1.00*** (0.09)	-1.05*** (0.09)	-1.44*** (0.09)
Observations	16071	16071	16071	16071	16071	16071

Note. Standard errors in parentheses, n=16071, * p<0.05, ** p<0.01, *** p<0.001. Standard Errors adjusted for 7 clusters in application year. Controlled for application year and position type.

Table 2-10 Probability Distribution of Predicted Performance Composite Deciles in terms of Actual Performance Composite Deciles

Actual Decile / Predicted Decile	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Expected Actual Decile of Performance composite for the Predicted Deciles
D1	0.19	0.15	0.10	0.11	0.06	0.09	0.08	0.09	0.06	0.06	4.54
D2	0.14	0.11	0.08	0.13	0.11	0.08	0.10	0.08	0.11	0.05	5.02
D3	0.13	0.13	0.11	0.10	0.07	0.13	0.09	0.13	0.05	0.05	4.91
D4	0.08	0.12	0.11	0.14	0.12	0.09	0.12	0.06	0.12	0.05	5.21
D5	0.07	0.10	0.10	0.10	0.18	0.12	0.07	0.07	0.10	0.09	5.42
D6	0.05	0.09	0.12	0.12	0.10	0.10	0.09	0.12	0.13	0.08	5.73
D7	0.04	0.08	0.09	0.09	0.14	0.11	0.11	0.11	0.13	0.11	6.09
D8	0.10	0.07	0.13	0.07	0.10	0.09	0.12	0.10	0.09	0.13	5.71
D9	0.08	0.05	0.09	0.08	0.08	0.09	0.11	0.13	0.09	0.19	6.22
D10	0.03	0.07	0.06	0.06	0.08	0.12	0.13	0.12	0.12	0.24	7.03

Table 2-11 Predicted Performance Composite and Expected Actual Decile Means for Those Recommended by Our Model and Actual Hires

	Actual hires	Recommended by	Difference
Predicted performance composite	0.11 (0.02)	0.37 (0.02)	0.26***
Expected actual decile	5.54 (0.02)	6.26 (0.00)	0.72***

Table 2-12 Comparison Between Outcomes of the Hired and Recommended Groups with Those of The Hired and Not-Recommended Groups

		Outcomes											
		Performance composite			Student evaluation			Expert observation			Value-added		
		Agree	Disagree	Difference	Agree	Disagree	Difference	Agree	Disagree	Difference	Agree	Disagree	Difference
Select on…	Performance composite	0.33	-0.11	**0.43***	0.08	-0.03	**0.11**	0.33	-0.11	**0.43***	0.16	-0.06	**0.22***
	Student evaluation	0.08	-0.01	**0.10**	0.20	-0.03	**0.23***	0.08	-0.01	**0.09**	-0.01	0.00	**-0.01**
	Expert observation	0.29	-0.08	**0.37***	0.10	-0.03	**0.13***	0.29	-0.08	**0.37***	0.21	-0.06	**0.27***
	Value-added	0.23	-0.09	**0.32***	0.05	-0.02	**0.07**	0.21	-0.08	**0.29***	0.20	-0.09	**0.29***
	Retention	-0.02	-0.24	**0.22***	-0.07	-0.05	**-0.02**	-0.05	-0.22	**0.17***	0.02	-0.07	**0.1**

Note. * p<0.05, ** p<0.01, *** p<0.001

Chapter 3: The Impact of Organizational Context on the Relationship between Staffing Events and Work Outcomes: Where Parallel Universes Meet

Sima Sajjadiani

3.1 Introduction

Despite their natural overlap, the bodies of literature on staffing and workplace context have evolved largely independently from one another (Nyberg & Ployhart, 2013; Ployhart, Hale, & Campion, 2014). Overall, the existing research on staffing has shown "a lack of concern with context" (Johns, 2006, p. 390). Most existing staffing research has been developed without consideration of the workplace context where important staffing events, such as hiring, employee dismissals, and layoffs, take place (with a few notable exceptions, e.g., Makarius & Stevens, 2017). The research and theories about staffing and workplace context have occurred in parallel universes, rarely intersecting with one another. Scholars in these fields tend to avoid the potentially troublesome interactions of the two subjects. This perhaps explains why Guion (2011) emphasizes the difficulty of incorporating context into staffing research in a chapter titled, "Challenges to Traditional Ways" (as cited by Ployhart et al., 2014, p. 24).

Recognizing the mutual avoidance of research on staffing and workplace context, strategic human resource (HR) scholars have called for a deeper examination of the intersection of these two domains (e.g., Johns, 2006; Nyberg & Ployhart, 2013; Ployhart, Hale, et al., 2014). Responding to this call, our research welcomes the challenge of incorporating analysis of context to the examination of staffing events. We acknowledge that although the two literatures portray staffing and context as parallel universes, they are destined to cross. Staffing decisions and subsequent staffing events do not take place within a vacuum, but instead within the context of a workplace. In the present research, we explore the way in which work outcomes are affected by strategic staffing decisions and subsequent staffing events (e.g., hiring, employee dismissals, layoffs). We examine whether the internal social and psychological contexts of the workplace and its external labor market influence the effects of staffing events on work outcomes.

We study work outcomes in terms of unit (store) performance and unit voluntary turnover rate. The HR-initiated staffing events that we consider include hiring, employee dismissals, and layoffs. Workplace context can comprise a broad range of phenomena beyond the level of the individual employee. We use available data to develop measures of, or proxies for, different social and psychological contexts of the workplace and its external labor market. Following existing research that highlights the effect of workplace collective rituals (e.g., Fehr, Fulmer, Awtrey, & Miller, 2017; Sheldon & Lyubomirsky, 2006), collective affect (e.g., Knight, Menges, & Bruch, 2018; Parke & Seo, 2017), and unemployment rate (e.g., Gerhart, 1990; Trevor, 2001) on work outcomes, we focus on the following: workplace appreciation ritual participation (a dimension of social internal context), workplace collective affective attitude (a proxy for psychological context), and unemployment rate in the metropolitan area in which the unit is located (an aspect of external labor market context). We consider how different levels of these dimensions of context elicit different responses to staffing events in terms of work outcomes. In other words, do staffing events differentially affect the work outcomes for a unit where workplace rituals are routine, or where employees show highly positive affective attitudes, or where the overall unemployment rate of the surrounding metropolitan area is relatively low compared to units whose contexts demonstrate the opposite features?

This work holds theoretical significance in that it will bring together the two parallel universes of research on staffing and workplace context. We hope to better the understanding of the role workplace context plays in the relationship between staffing events and work outcomes. This will be valuable to organizations when they attempt to assess their context in an effort to provide a supportive work environment. In practice, organizations operate upon an assumed mutual effect between context and staffing decisions. This makes the neglect of the academic literature on this topic all the more surprising (Ployhart, Hale, et al., 2014, p. 23). Our research answers the question of whether improvements in workplace rituals and collective affective attitude can be leveraged by organizations to alter the consequences of staffing events. The present research also assesses the way in which monthly local unemployment rates influence the response to staffing events.

While we draw upon existing research and theory, our study advances the strategic HR management literature in several important ways. First, this research is among the first to take into account both the workplace internal socio-psychological contextual factors and external labor market. As such, it contributes to an emerging direction in the strategic HR literature that acknowledges the importance of context in understanding staffing events (Hausknecht, Trevor, & Howard, 2009; Nyberg & Ployhart, 2013; Ployhart, Hale, et al., 2014; Trevor, 2001). Our model and data provide a unique opportunity to address instances of both internal (i.e., outside the individual but within the workplace) and external (i.e., outside the workplace) contexts. Second, our research theoretically and empirically explores staffing events and work outcomes at the unit level, joining a group of recent studies that have shifted attention from the individual level to the unit level in evaluating these events (e.g., Hausknecht & Trevor, 2011; Nyberg & Ployhart, 2013). Third, we take a systemic approach to understanding the mutual effects of the components of our model (i.e., staffing events, contextual factors, and unit performance). We evaluate the effects of both HR-initiated staffing events (i.e., hiring, employee dismissals, and layoffs) and employee-initiated events (i.e., voluntary turnover) on each other and on unit performance. Fourth, we expand the scope of an emergent set of studies (Call, Nyberg, Ployhart, & Weekley, 2015; Reilly, Nyberg, Maltarich, & Weller, 2014) that evaluate staffing events from a dynamic point of view. Using dynamic system analysis, we model the impulse response function for each variable to evaluate the duration and magnitude of the effects of staffing events on outcomes. As such, our analysis not only examines the effects of staffing events on work outcomes under different contextual situations, but also demonstrates the duration of effects and the change in their strength over time.

To empirically evaluate our research questions, we use longitudinal personnel, financial, and pulse survey data collected from 1,837 stores (work units) of a large national retailer over a 22-month period. We also examine the duration and significance of staffing events' effects on work outcomes by evaluating the components of our model as endogenous, co-evolving parts of a dynamic system whose effects interact and unfold over time.

3.2 Hypothesis Development

An emergent set of studies (e.g., Call et al., 2015; Makarius & Stevens, 2017; Reilly et al., 2014) examine the consequences of staffing events under the rubric of human capital flow. The literature on human capital flow focuses on the movement of individuals in or out of units (Nyberg & Ployhart, 2013). HR-initiated staffing events (e.g., hiring, employee dismissals, and layoffs) and employee-initiated staffing events (e.g., voluntary turnover) are the major sources of human capital flow in and out of units. The majority of studies on human capital flow have focused on voluntary turnover through the lens of the Context-Emergent Turnover (CET) theory, a collective human capital theory (Nyberg & Ployhart, 2013). CET theory considers the effect of employee movement in and out of the organizations on important organizational outcomes. It conceives of human capital flow as a dynamic and holistic process that is embedded "within the nomological network of the human capital resource" (Nyberg & Ployhart, 2013, p. 109). CET theory also accounts for the moderation effects of context on the relationship between collective turnover and its outcomes.

CET theory informs the present study's explanation of the relationship between HR initiated staffing events, unit-level voluntary turnover, and performance. CET theory also informs our study's emphasis on the importance of context in understanding the consequences of human capital flow.

3.2.1 Staffing Events and Collective Work Outcomes

Staffing events are among the most important factors that can affect employees at work. Event system theory (Morgeson, Mitchell, & Liu, 2015) suggests that events can change the behavior of employees at different organizational levels. The effects brought about by events evolve over time. Several studies offer evidence in support of affective, attitudinal, and behavioral challenges faced by those directly or indirectly impacted by workplace changes. These challenges exist whether the transformations involve major reengineering (e.g., downsizing), or minor reorganization (e.g., the addition of new team members) (Mossholder, Settoon, Armenakis, & Harris, 2000; O'Neill, Lenn, Neill, & Lenn, 1995; Rafferty & Restubog, 2010). Research has shown that change is portrayed and perceived mostly in negative terms among employees because change is often accompanied by uncertainty about the future, unfamiliarity, and disruptions (Kabanoff, Waldersee, & Cohen, 1995; Mossholder et al., 2000). We expect that this is also true about the changes caused by staffing events. Similar to other workplace changes, we expect that staffing events disrupt employees' routines. As such, units are expected to experience operational disruptions in the wake of staffing events, at least for a while until they adapt to the new situation (Hausknecht et al., 2009; Watrous, Huffman, & Pritchard, 2006).

In addition to unit performance, workplace changes are typically associated with a change in voluntary turnover. For instance, Holtom, Mitchell, Lee, and Inderrieden (2005) found that events such as corporate mergers and layoffs significantly increase employee voluntary turnover. These findings can be interpreted in light of the unfolding model of turnover (Davis et al., 2015; Lee, Thomas W.; Mitchell, 1994; T. W. Lee et al., 1999; T. W. Lee, Mitchell, Wise, & Fireman, 1996; Trevor & Nyberg, 2008). This model considers these workplace events as shocks to the system that trigger psychological reactions, which in turn lead to voluntary turnover. Thus, the literature gives us reason to expect that units experience a change in the rate of voluntary turnover in the wake of disruptive staffing events.

We next discuss unit responses in terms of unit performance and turnover rate to specific unit-level HR-initiated staffing events, including, (1) hiring rates, (2) rate of dismissal of unit members for cause, (3) layoffs/downsizing rates, and (4) rate of voluntary turnover. In the following sections we also discuss the way in which context variables can moderate the unit's response to staffing events.

Hiring. It is widely believed that the arrival of newcomers results in positive organizational change due to the introduction of new ideas, energy, and challenges to routine (Wang & Zatzick, 2018). Despite this idea, research has shown that newcomer arrival does not immediately translate into positive outcomes, as teams tend to resist change and have a strong preference for familiarity (Baer, Leenders, Oldham, & Vadera, 2010; Rink, Kane, Ellemers, & Van Der Vegt, 2013). Team members trust those whom they know (Ellemers, De Gilder, & Haslam, 2004; Liang, Moreland, & Argote, 1995; van der Vegt, Bunderson, & Kuipers, 2010). Research has also shown that it takes time for newcomers to fit in and become trusted by their incumbents. Thus, collaboration and the fluid exchange of knowledge are not immediate (Tzabbar, Aharonson, & Amburgey, 2013; Wang & Zatzick, 2018). Levine and Moreland (2006) have suggested that teams are reluctant to accept newcomers because this staffing event triggers a disruption. In the event of newcomers joining the unit, incumbents are often burdened with training and socializing the new employees who may lack knowledge and experience (Batt, 2002; Michele Kacmar, Andrews, Van Rooy, Chris Steilberg, & Cerrone, 2006). While newcomers take time to adapt to their roles, unit dynamics may suffer due to their lack of proficiency. Proficiency can also be negatively impacted when incumbents are asked to divide resources between their own tasks and getting newcomers up to speed (Hausknecht et al., 2009; Shaw, Delery, Jenkins, & Gupta, 1998).

Thus, it is reasonable to expect a decrease in unit performance in the wake of newcomers' arrival, at least for some time. We also expect this effect to increase in strength with an increase in the rate of newcomer arrivals. The higher the rate of new hires, the more disruption to unit routines and therefore the more attention and division of resources demanded from incumbents.

When it comes to voluntary turnover rate in response to the rate of new hires, research has theoretically (Jovanovic, 1979) and empirically (Farber, 1994; Kammeyer-Mueller & Wanberg, 2003) demonstrated that recently hired employees are prone to turnover. When starting a new job, new hires often try to decide whether the job and the organization is a good match for them. If they do not perceive a good fit with the job or the organization, they may decide to leave. Therefore, we expect higher rates of new hires to be correlated with higher collective voluntary turnover in the subsequent month.

Hypothesis 1: Hiring (a) is negatively related to unit performance in the subsequent month and (b) positively related to voluntary turnover rate in the subsequent month.

Employee dismissal. Employee dismissal is defined as employee termination due to poor performance, lack of integrity, violation of rules and policies, or other similar reasons (Batt & Colvin, 2011; McElroy, Morrow, & Rude, 2001). There are only a handful of studies that have addressed employee dismissal and its effects on unit performance or subsequent turnover rates. These studies point to two distinct effects that occur in opposite directions: while dismissals tend to negatively affect the unit due to operational difficulties (including the extra workload to be shouldered by the continuing employees), dismissal of ‘bad apples’ tend to have a positive effect on the affective state of the unit.

Although theoretical studies predominantly argue for a positive relationship between employee dismissal and unit performance (McElroy et al., 2001; Simón, Sivatte, Olmos, & Shaw, 2013; Trevino, 1992), a negative link between the two has been reported by empirical research. For example, Trevino’s (1992) theoretical paper considered organizational punishments, including employee dismissal, to be social events that influence both the direct targets of punishment and their observers. Drawing upon social learning theory (Bandura, 1971), Trevino (1992) explained that observers would adjust their future behaviors to avoid similar punishments. She argued that punishments will have positive effects on observers’ outcomes, especially if they believe the punishment was just. McElroy et al. (2001) used similar arguments to hypothesize a positive relationship between employee dismissals and unit performance.

The empirical findings, however, do not support the theorized positive relationship between dismissal and unit performance. For example, the empirical results reported by McElroy et al. (2001) found that employee dismissals were associated with lower subsequent unit performance. Relatedly, Batt and Colvin (2011) showed that firms with higher dismissal rates reported lower levels of customer service satisfaction. One explanation that may account for these results is operational difficulties caused by the higher work burden placed on the remaining employees in the wake of dismissals. This additional work pressure can neutralize the positive consequences of the dismissal of poor performers or even decrease the unit performance for some time. Thus, we hypothesize that following the dismissal of 'bad apples', the continuing employees will work harder to avoid similar punishments. But in the short run, because of the extra work burden placed on the continuing employees, it is reasonable to anticipate a relatively small decrease in overall unit performance.

When it comes to the effect of dismissals on voluntary turnover, we expect a negative relationship between the two, because of the positive effects of dismissals on the affective state of the unit. Barsade (2002, p. 669) explained that units could be affected by disruptive members, "the proverbial 'bad apple' who causes the entire group to feel apprehensive, angry, or dejected, leading to possible morale and cohesion problems, unrealistic cautiousness, or the tendency to disregard creative ideas, thus 'spoiling the barrel.'" As such, following the dismissal of poor performers, the affective state and job attitudes of continuing unit members are expected to improve (Mowday, 1981). Numerous studies have shown that job attitudes, especially job satisfaction and organizational commitment, are among the most important predictors of voluntary turnover (e.g., Mitchell, Holtom, Lee, Sablynski, & Erez, 2001; Trevor, 2001). If employee dismissal results in a net increase in overall job satisfaction, we expect a subsequent decrease in unit level voluntary turnover. This will hold if the increase in job satisfaction resulting from the dismissal of 'bad apples' outweighs the inconvenience of the additional work burden placed on continuing employees.

We believe it is reasonable to expect a net increase in job satisfaction as a result of the dismissal of disruptive employees. Disruptive employees create dysfunctional units in which members are more likely to be dissatisfied. To detach themselves from the unpleasant workplace, employees in dysfunctional units engage in withdrawal behaviors. As a result, it is expected to observe higher rates of absenteeism and turnover rates in these units (Cole, Walter, & Bruch, 2008; Felps, Mitchell, & Byington, 2006; Pelled, 1999). The dismissal of disruptive employees will help to reduce these withdrawal behaviors. We expect that higher rates of disruptive employee dismissal will be associated with lower rates of withdrawal behaviors, including voluntary turnover rate.

> ***Hypothesis 2:*** *Employee dismissals are (a) negatively related to unit performance in the subsequent month and (b) negatively related to voluntary turnover in the subsequent month.*

Layoffs. In general, organizations carry out reductions in their workforce and layoffs to improve their financial performance. Evidence has shown that improvements in performance occur when the level of inefficiency is high and the organization executes layoffs proactively (E. G. Love & Nohria, 2005). Simón et al. (2013) theorized that layoffs increase unit performance because these events are usually planned in advance and organizations typically address the redistribution of human capital resources before implementing layoffs.

However, to better understand the effects of layoffs, we should take into account the survivors' reaction to these events. Research has shown that employees perceive organizational change negatively. This negative reaction is stronger when organizational change involves significant and salient events, such as layoffs and downsizing (Morgeson et al., 2015; Mossholder et al., 2000). Extensive research has demonstrated that those who experience job loss, including the victims of layoffs, suffer from stress, pessimism, social isolation, and despair (Leana & Feldman, 1992; Wanberg, 2012). Classen and Dunn (2012) found that mass layoffs or establishment closure significantly increased the chance of death by suicide. Therefore, it is reasonable to expect an increase in negative affect and attitude in the wake of news of layoffs. The same also holds for the case of the employees who remain behind. Research has shown that these individuals face increases in stress, perceive threats to their future employment, and experience feelings of anger, anxiety, cynicism, and resentment (Brockner et al., 1997; Brockner, Grover, Reed, & Lee Dewitt, 1992; O'Neill et al., 1995; Oreg, Vakola, & Armenakis, 2011).

When it comes to the attitudinal consequences of layoffs, several studies have found lower levels of organizational commitment (Brockner, Grover, & Reed, 1987; Knudsen, Johnson, Martin, & Roman, 2003; Trevor & Nyberg, 2008) and job satisfaction

(Armstrong-Stassen, 2002; Luthans & Sommer, 1999) among layoff survivors. Other studies found that layoff survivors experience affective and operational disruptions because layoffs can deplete human capital and put more pressure on those who remain behind and need to distribute their resources to cover the tasks of those who left the organization (Hausknecht et al., 2009; Shaw, Duffy, Johnson, & Lockhart, 2005; Watrous et al., 2006).

Since layoff is linked to lower levels of job security, organizational commitment, and job satisfaction, it is reasonable to believe that the employees who recently survived a layoff will begin to more actively search for alternative jobs. Davis et al. (2015) drew on the literature on the unfolding model of turnover to characterize layoff events as shocks that motivate layoff survivors to reevaluate their alternative options and available opportunities. This motivated attention to availabilities in the labor market increases the likelihood of voluntary turnover among layoff survivors. Moreover, several studies have found a positive association between layoffs and the subsequent voluntary turnover rate among layoff survivors. This association is likely due to factors such as reduced perception of job security, reduced organizational commitment, and decrease in job satisfaction (Batt, Colvin, & Keefe, 2002; Trevor & Nyberg, 2008).

Overall, the literature suggests a negative relationship between the rate of layoff and performance and a positive relationship between the rate of layoff and voluntary turnover. It is worth noting that layoff rate in our data does not include the terminations of seasonal employees. Although a retailer is the focus of the present study, the cyclical nature of seasonal employee movement is not part of the layoff rate that we use. Thus, we are justified in drawing upon studies that may have been conducted in different settings.

Hypothesis 3: *Unit layoffs are (a) negatively linked to unit performance in the subsequent month and (b) positively linked to unit voluntary turnover in the subsequent month.*

Voluntary turnover. Similar to other organizational changes brought about by HR-initiated staffing events, research has shown that voluntary turnover, an employee-initiated staffing event, creates an operational disruption that leads to lower unit performance (Hausknecht et al., 2009; Michele Kacmar et al., 2006). Hausknecht et al. (2009) found empirical evidence in support of the negative relationship between unit turnover and customer service quality. They explained that turnover depletes firm-specific knowledge and experience from the unit. It takes time for the new replacements to learn the required knowledge and become proficient. During this period, customers receive service from less knowledgeable and less experienced employees, leading to a subsequent decrease in customer service quality. Moreover, turnover puts pressure on other unit members as they have to divide their resources and attention to cover the tasks of those who have left the unit. This pressure can have negative effects on unit performance (Hausknecht et al., 2009; Shaw et al., 2005).

We also expect that high rates of voluntary turnover increases the voluntary turnover rate in the subsequent month. Contagion turnover theory (Felps et al., 2009) describes the “snowball effects” of voluntary turnovers on the remaining employees. Quitting a job involves high levels of risk and uncertainty. To make such a risky decision, individuals seek more information by comparing themselves to their colleagues. Other employees' engagement in job search behaviors signals to the remaining employees that other opportunities are available. This information results in an increase in the number of subsequent voluntary turnovers.

Job embeddedness theory (Mitchell et al., 2001) also explains the subsequent increase in voluntary turnover rate. The more employees feel embedded in their job, the lower the risk of their voluntary turnover. The social network and extent to which employees are connected to their colleagues is one of the critical forces that keep them embedded in their present jobs. Therefore, the higher the rate of voluntary turnover in the unit, the less likely that employees are embedded in their jobs. This in turn increases the chance of voluntary turnover rate among other employees.

Hypothesis 4: *Unit turnover is (a) negatively related to unit performance in the subsequent month and (b) positively related to voluntary turnover rate in the subsequent month.*

3.2.2 Workplace Internal and External Context and Collective Work Outcomes

Workplace context is defined as situational internal and external opportunities and constraints that impact workplace outcomes (Johns, 2006; Self, Armenakis, & Schraeder, 2007). The internal context includes characteristics within the workplace that are external to individual employees but influence their beliefs, attitudes, affect, and behaviors. Rituals, norms, and socio-psychological environment are considered to be workplace internal contextual factors (Nyberg & Ployhart, 2013; Ployhart, Hale, et al., 2014).

External workplace context takes account of the surrounding environment external to the workplace (Cappelli & Sherer, 1991; Johns, 2006). Examples of external dimensions of workplace context include socio-economic background, labor market characteristics, and laws or regulations that influence the unit's performance and survival (Rafferty & Restubog, 2010). Similar to internal context, external context has been shown to influence unit outcomes (Self et al., 2007).

Different manifestations of workplace context, internal or external, are experienced beyond individual differences at a collective level in organizations or work units (Johns, 2006; Ployhart, Hale, et al., 2014; Schein, 2010). These contextual factors serve to establish and maintain conformity and consistency of behaviors and attitudes in a workplace (Bowen & Ostroff, 2004; Parke & Seo, 2017).

In the present study we use available data to develop measures of, or proxies for, different aspects of context. We evaluate their direct effects on work outcomes as well as their moderating effects on the relationship between staffing events and unit outcomes. We use unit level participation in a daily appreciation ritual as a proxy for collective appreciation in units (a measure of social internal context). We also use collective affective attitude as a proxy for affective context. For a measure of the external context, we use monthly unemployment rates in each unit's corresponding metropolitan area. In the next section we discuss each context variable and its direct relationship with unit outcomes in more detail.

Appreciation ritual participation and unit outcomes. In general, workplace rituals help to establish emotional solidarity, cohesion, and community bonds (Islam &

Zyphur, 2009; A. C. T. Smith & Stewart, 2011). HR-initiated formal appreciation programs (a specific form of workplace ritual) are attracting growing attention in both research and practice. These programs are “occasions in which organizations have planned and institutionalized opportunities to endow individuals with expressions of positive affirmation” (Roberts, Dutton, Spreitzer, Heaphy, & Quinn, 2005, p. 718). Examples of actual appreciation programs include meetings where managers share team members’ core strengths and contributions to the organization (Dutton, 2003; Roberts et al., 2005) and appreciation websites available for employees to share their gratitude for particular colleagues (J. Smith, 2013). Collective appreciation at the unit level emerges from persistent experience of gratitude at the individual level (Fehr et al., 2017). As such, “to measure persistent gratitude, scholars must assess the frequency with which employees tend to experience gratitude in the workplace” (Fehr et al., 2017, p. 375).

Our data provides a measure of self-reported participation in a daily appreciation ritual that has been part of the organization’s culture for more than a decade. This appreciation ritual fits Roberts et al.’s (2005, p. 718) definition of formal appreciation programs mentioned above (for details of the ritual, see section 3.3.2).

Following Fehr et al.’s (2017) conceptualization of collective appreciation, we consider the monthly rate of participation in the daily appreciation ritual as an indicator of collective appreciation in the unit. This variable is informative as an indicator of the strength of collective appreciation norm in the workplace as it quantifies the proportion of employees who have been exposed to the unit’s daily ritual. Exposure to a unit’s ritual is an exogeneous variable because only employees who happened to be present in the store at the time of opening attend the ritual. This exogeneous variation in exposure to the ritual provides a unique opportunity to evaluate the effects of formal appreciation programs on collective outcomes.

It has been suggested that appreciation rituals and gratitude programs improve subjective well-being, team engagement, and cohesion by increasing the collective sense of gratitude and appreciation among employees (Fehr et al., 2017; Sheldon & Lyubomirsky, 2006). However, there is a dearth of empirical research that evaluates the effect of collective appreciation on unit work outcomes (Fehr et al., 2017). Waters (2012) used the integrity and gratitude sub-scale of the Positive Practices Scale ("At my workplace, we express gratitude to each other") (Cameron, Bright, & Caza, 2004) to show that institutionalized gratitude is positively related to collective job satisfaction. Increase in employee gratitude has also been shown to result in high-quality relationships, team cohesion, prosocial behavior among members, and perceived organizational embeddedness (Algoe, Haidt, & Gable, 2008; Ng, 2016; Spence, Brown, Keeping, & Lian, 2013).

Several mechanisms can account for the relationship between feelings of appreciation (gained through appreciation rituals) and positive work outcomes. Greater workplace cohesion is associated with higher levels of performance (Beal, Cohen, Burke, & McLendon, 2003) and lower unit turnover rates (George & Bettenhausen, 1990). Attention to the positive qualities of others makes team members more willing to work with each other and strengthens their relationships and cohesion (Algoe et al., 2008; Watkins, 2004). Promoting positive affect and subjective well-being increases the ability of employees to cope with stressful events and challenges (Fehr et al., 2017; Kaplan et al., 2014; Lambert & Fincham, 2011; Wood, Froh, & Geraghty, 2010; Wood, Maltby, Gillett, Linley, & Joseph, 2008).

Hypothesis 5: *Participation in a unit appreciation ritual is (a) positively linked to unit performance in the subsequent month and (b) negatively linked to unit voluntary turnover in the subsequent month.*

Collective affective attitude and collective work outcomes. In this section we first introduce the concept of affective attitude. We then explain how this notion is conceptualized at the unit-level (collective affective attitude). Lastly, we explore the relationship between collective affective attitude and unit work outcomes.

We broadly define affective attitude as the way employees feel at work. Affect and attitude are distinct yet closely related constructs in the organizational behavior literature. Affect is a significant component of job attitude (George, 1989; Judge, Hulin, & Dalal, 2009; Weiss & Cropanzano, 1996) and both affective states (e.g., happiness, frustration) and organizational attitudes (e.g., job satisfaction, organizational commitment, and engagement) influence employee behavioral responses to various events (Judge et al., 2009; Judge & Kammeyer-Mueller, 2012; Schleicher et al., 2011; Weiss & Cropanzano, 1996).

We aggregate individuals' affective attitude to the unit level and refer to this measure as collective affective attitude. It provides an indication of internal affective context in our model. There are several lines of study that argue for the inclusion of constructs beyond the individual level that typically fall under the umbrella of affect. The literature on organizational behavior points to a collective affective tone that exists at the unit level, ranging from smaller work groups to larger collectives. Collective affective tone is the construct that is most similar to collective affective attitude used in the present study. While the collective affective tone of smaller groups is realized through interactional micro mechanisms, the collective affective tone of larger collectives is the result of macro mechanisms, such as HR practices at the organizational level (Knight et al., 2018).

The research that argues for a collective affective tone that is created by interactional micro mechanisms includes those informed by attraction-selection-attrition and emotional contagion process theories. George (1990) has defined the construct of collective affective tone as a homogeneous affective state that is collectively experienced by group members. Using the attraction-selection-attrition theory, George and her colleagues (2002) argued that organizations attract and select similar employees in terms of personality and job attitudes. Over time, those who are less similar to other members will leave the workplace. The resulting homogeneity among unit members leads to consistency in the unit affective tone (Collins, Jordan, Lawrence, & Troth, 2016). Moreover, the emotional contagion process theory (Barsade, 2002; Sy, Saavedra, & Cote, 2005) asserts that the emotions of one person in a group can spread to other members, leading to a consistent and shared affective tone. Several studies have empirically supported this theory (e.g., Ilies, Wagner, & Morgeson, 2007; Totterdell, 2000) and the literature acknowledges that “the aggregation of individuals’ affect can meaningfully represent the “affective tone” of the team” (Collins et al., 2016, p. 167).

While the theory and research on collective affective tone has until recently focused on smaller work groups, an emerging set of studies has begun to link collective affective tone to the organization’s larger context. This suggests an overarching workplace affective context that is facilitated by HR macro mechanisms. This affective context is characterized by consistent affect and feeling states across employees. The overarching affective tone functions as a contextual resource and influences unit work outcomes (Barsade & O’Neill, 2014; Knight et al., 2018; Menges & Kilduff, 2015; O’Neill & Rothbard, 2017; Parke & Seo, 2017). Knight, Menges, and Bruch (2018, p. 191) define this overarching affective tone as “consistent positive and negative feelings held in common across organizational members.”

Research has generally found a positive relationship between collective affective tone and unit outcomes (Barsade, 2002; Cole et al., 2008; Mason & Griffin, 2003; Sy et al., 2005; Tsai, Chi, Grandey, & Fung, 2012). Positive collective affective tone has been shown to be positively linked to unit performance (Barsade, 2002; Hmieleski, Cole, & Baron, 2011; Tanghe, Wisse, & van der Flier, 2010), and negative collective affective tone to be negatively associated with unit performance (Cole et al., 2008). Aspects of unit performance examined in the literature include task performance (Bramesfeld & Gasper, 2008; Knight, 2015) and prosocial behavior (George & Bettenhausen, 1990). Furthermore, work outcomes are shown to be linked to the affective aspects of job satisfaction (Judge et al., 2001). Judge et al. (2001) drew on extant studies (Brief, Butcher, & Roberson, 1995; Isen & Baron, 1991; Staw & Barsade, 1993) to explain the mechanism through which positive affect is related to better performance. They argue that “individuals who like their jobs are more likely to be in good moods at work, which in turn facilitates job performance in various ways, including creative problem solving, motivation, and other processes (Judge et al., 2001, p. 392).

To the best of our knowledge, there is no study that has directly evaluated the relationship between unit affective attitude or affective tone and unit turnover rate. However, there is evidence that contextual factors, including affective context, can influence collective withdrawal behaviors (Bakker, Demerouti, & Verbeke, 2004; Knight et al., 2018), which are considered to be precursors of turnover (Griffeth et al., 2000; Mason & Griffin, 2003). Although not explicitly focused on turnover, a few studies have discussed the direct or indirect effects of team affective tone on team-level withdrawal behaviors. For example, Mason and Griffin (2003) found that team positive affective tone was negatively linked to team level absenteeism. George and Bettenhausen (1990) demonstrated that a team leader’s positive affect negatively influenced team voluntary turnover. They explained that a possible mechanism for this relationship is that leaders with positive affect created positive work environments that would negatively influence overall turnover rate.

> ***Hypothesis 6:*** *Collective affective attitude is positively related to (a) unit performance in the subsequent month and (b) negatively related to unit voluntary turnover rate in the subsequent month.*

Unemployment rate and unit work outcomes. Labor market characteristics, particularly unemployment rates, are crucial in understanding employees' alternative options and the level of competition for jobs (Cappelli & Sherer, 1991; Hausknecht & Trevor, 2011; Johns, 2006; Ployhart, Hale, et al., 2014). The local unemployment rate has the potential to either positively or negatively impact unit performance in retail stores. On one hand, higher local unemployment rates signal lower purchasing power. Therefore, in areas where the local unemployment rate is high, it is reasonable to see a decrease in sales and unit financial performance. On the other hand, higher local unemployment rates indicate fewer job opportunities in the area. Thus, it is expected that employees will work harder to keep their current jobs because the likelihood of finding a similar opportunity elsewhere is lower. This argument is in line with efficiency wages theory (Shapiro & Stiglitz, 1984) that proposes workers are incentivized to exert more effort if they know that they cannot find a better or similar job elsewhere. Moreover, Williams and Livingstone (1994) reported in their meta-analysis that unemployment rates are positively related to individual performance. As such, it is plausible that unemployment rates are also positively related to unit financial performance.

In sum, it is likely that high levels of unit performance are associated with high unemployment rates due to supply-side effects of the labor market. However, the effect of local unemployment rates on unit performance may not be powerful enough to be detected due to the low purchasing power of consumers (demand-side effect). Thus, we refrain from suggesting a hypothesized positive relationship between local unemployment rate and unit performance.

Several studies have shown that labor market effects of the local unemployment rate influence employees' decisions about whether to leave their job or not. In particular, these studies found that lower rates of local unemployment are associated with a high turnover rates because employees have more alternative options (Gerhart, 1990; Kammeyer-Mueller, Wanberg, Glomb, & Ahlburg, 2005; Trevor, 2001).

Hypothesis 7: *Unemployment rate is negatively related to unit turnover rate in the subsequent month.*

3.2.3 Moderating Effects of Context on the Link between Staffing Events and Work Outcomes

Appreciation Rituals. Appreciation programs and rituals are formal programs in which appreciation is expressed for the contribution of employees (Fehr et al., 2017). Research has shown that feeling appreciated and grateful promotes high-quality relationships, cohesion, and prosocial behavior among employees (Algoe et al., 2008; Brun & Dugas, 2008; Di Fabio, Palazzeschi, & Bucci, 2017; Spence et al., 2013), increases perceived organizational embeddedness (Ng, 2016), and improves positive affect and subjective well-being through shifting individuals' focus to positive events and increasing their ability to cope with stressful events and challenges (e.g., Fehr et al., 2017; Kaplan et al., 2014; Lambert & Fincham, 2011; Wood et al., 2010, 2008). Higher levels of participation in appreciation rituals are therefore expected to mitigate the negative effects of high rates of newcomer arrivals, layoffs, and voluntary turnover on subsequent unit performance and voluntary turnover, through promoting high-quality relationships, higher levels of gratitude, cohesion, and prosocial behavior among employees as well as improving positive affect and subjective well-being. For example, appreciation rituals, through the resulting group cohesion, may mitigate the negative effects of the arrival of new hires on unit performance. George and Bettenhausen (1990) showed that team cohesion results in higher levels of helping and prosocial behaviors among employees. Therefore, it is possible that more cohesive units are better able to adjust to the arrival of newcomers by helping new members get quickly up to speed on the tasks involved in their new jobs.

Several studies have theoretically explained (Jovanovic, 1979) and provided empirical evidence (Farber, 1994; Kammeyer-Mueller & Wanberg, 2003) that there is a higher rate of voluntary turnover among those who recently joined an organization. This may be due to the fact that they do not perceive a good fit between themselves and the job or are not able to adjust to the organization’s context. These issues may be mitigated in a positive and cohesive work environment where employees are more engaged in prosocial and helping behaviors. In these contexts, incumbents are more open to change, tend to focus on positive aspects of the arrival of the newcomers, and are more willing to help the newcomers to adjust. For example, Ng (2016) showed in a longitudinal study that perceived respect and feelings of gratitude among newcomers increases their perceived organizational embeddedness over time, which in turn decreases turnover.

Layoffs are one of the most stressful events in organizations and can negatively influence survivors’ sense of psychological safety, job security, and organizational commitment (Brockner et al., 1987; Trevor & Nyberg, 2008). Several studies have empirically demonstrated that persistent feelings of gratitude, which may be promoted by participation in appreciation rituals, can shift individuals' focus to positive events and increase their ability to cope with stressful events (e.g., Fehr et al., 2017; Kaplan et al., 2014; Lambert & Fincham, 2011; Wood et al., 2010, 2008). Furthermore, Mohr, Young, and Burgess (2012) found that group-oriented workplace cultures characterized by cohesion, mutual trust, and commitment mitigates the negative effects of voluntary turnover rate on unit performance.

In the sections above, we extensively discussed the way in which participation in appreciation rituals is expected to have a positive effect on unit performance and a negative effect on voluntary turnover rate. Thus, we hypothesize that the positive effects of appreciation rituals mitigate the negative consequences of layoffs on unit performance and turnover rate.

Finally, Nyberg and Ployhart (2013) have suggested that a strong climate for teamwork can mitigate the negative effects of turnover on unit performance because those who stay behind now belong to a more cohesive work unit. Thus, they are more likely to work together to cover the responsibilities of those who left the unit. Although they did not find support for this suggestion, Hausknecht et al. (2009) have similarly hypothesized that unit cohesion moderates the relationship between turnover and unit performance. They attributed this mediating effect to the fact that in cohesive units, the continuing members would share the tasks between themselves and help each other move the work forward.

Hypothesis 8: *Appreciation ritual participation mitigates the negative effects of (a) hiring, (b) layoffs, (c) employee dismissal, and (d) voluntary turnover rates on* *unit performance in the subsequent month. Appreciation ritual participation also mitigates the increase in subsequent voluntary turnover rate due to (e) hiring, (f) layoffs, and (g) unit voluntary turnover rate. Appreciation ritual participation (h) boosts the decrease in voluntary turnover rate in the subsequent month due to employee dismissal.*

Collective Affective Attitude. The link between positive affective tone and positive attitudinal and behavioral outcomes has been well established in the literature on organizational behavior. Several studies have demonstrated that collective affective tone is positively associated with unit cohesion (Barsade, Ward, Turner, & Sonnenfeld, 2000; Lawler, Thye, & Yoon, 2000; Magee & Tiedens, 2006). For example, Barsade et al. (2000, p. 807) have suggested that positive affective tone in the workplace results in cooperation and cohesion among employees through “greater feelings of familiarity, attraction, and trust.” Likewise, Magee and Tiedens (2006) found that the positive or negative emotions of the individuals within a unit predict the unit’s level of cohesion.

Other studies have connected collective affective tone to work engagement (Christian, Garza, & Slaughter, 2011; Costa, Passos, & Bakker, 2014; Hülsheger & Schewe, 2011; Tsai et al., 2012). For example, Tsai et al. (2012) explained that unit positive affective tone creates a comfortable and pleasant work environment, leading to an increase in unit-level engagement. Similarly, Costa, Passos, and Bakker (2014, p. 423) have shown that unit work engagement, a “shared positive emergent state of work-related well-being,” is associated with positive affective tone.

Finally, research has also explored the relationship between collective affective tone and prosocial behaviors (George, 1991; George & Bettenhausen, 1990). George (1991) has shown that positive affect is linked to more prosocial behaviors among sales employees. Relatedly, George and Bettenhausen (1990) have demonstrated that collective negative affect is negatively associated with prosocial behaviors.

Therefore, we predict that collective affective attitude, perhaps through heightened unit cohesion, mitigates the negative effects of the arrival of new hires on unit performance. In other words, more cohesive units are expected to better adjust to the arrival of newcomers by helping new members acquire required skills and knowledge.

Also, we expect that units with higher levels of collective affective attitude are more easily able to overcome the consequences of human capital loss (e.g., employee dismissal, layoffs, or voluntary turnover) because they collaborate and share their resources more generously to make up for the responsibilities of those who left.

Hypothesis 9: *Positive collective affective attitude mitigates the negative effects of (a) hiring, (b) layoffs, (c) employee dismissal, and (d) voluntary turnover on unit performance in the subsequent month. Positive collective affective attitude also mitigates the increase in subsequent voluntary turnover rate due to (e) hiring, (f) layoffs, and (g) unit voluntary. Positive collective affective attitude (h) boosts the decrease in voluntary turnover rate in the subsequent month due to employee dismissals.*

Unemployment Rate. The unemployment rate of the surrounding local area is a crucial factor in understanding employees' alternative options and the level of competition for jobs (Cappelli & Sherer, 1991; Hausknecht & Trevor, 2011; Johns, 2006; Ployhart, Hale, et al., 2014). We expect that the local unemployment rate will influence employees' turnover decisions in response to staffing events. When the local unemployment rate is high, the voluntary turnover rate will be lower because employees perceive fewer alternative opportunities. On the other hand, when the local unemployment rate is low, the voluntary turnover rate will be high. This is because the likelihood of finding other opportunities at different organizations is likely to be higher. In these situations, newcomers who do not perceive a good fit between themselves and the organization are more likely to leave. Similarly, layoff survivors who are not satisfied with their job or feel less secure are more likely to leave to find an alternative job.

We do not suggest any moderating effects of local unemployment rate on the relationship between staffing events and unit performance. This is because the unit performance of retail stores may either be positively or negatively impacted by higher unemployment rates. On one hand, higher unemployment rate signals fewer job opportunities elsewhere. Therefore, it is expected that employees will work harder to keep their job and unit performance is expected to increase accordingly. On the other hand, higher local unemployment rate signals lower purchasing power in the location. Therefore, it is reasonable to predict a decrease in sales (unit performance) when the local unemployment rate is high.

Hypothesis 10: *Unemployment rate mitigates the increase in voluntary turnover rate in the subsequent month due to (a) hiring, (b) layoffs, and (c) voluntary turnover rate. Unemployment rate boosts the decrease in voluntary turnover rate in response to (d) employee dismissals.*

3.2.4 Temporal and Dynamic Analysis

Temporal and dynamic analyses help researchers to better understand why certain relationships exist and how they change over time (George & Jones, 2000; T. H. Lee, Gerhart, Weller, Trevor, & Ellig, 2008; Weller, Holtom, Matiaske, & Mellewigt, 2009). Context Emergent Turnover (CET) theory (Nyberg & Ployhart, 2013) and Event System theory (EST) (Morgeson et al., 2015) emphasize the importance of temporal and dynamic analyses in the evaluation of events. EST explains that events are to be understood as dynamic because as they unfold over time and interact with different components of the system, their overall strength and effect can change. EST highlights the strength of an event as a function of its novelty, the level of disruption it causes in the status-quo, and its criticality. The stronger the event, the longer its effects will last. Likewise, in evaluating the dynamic, mutual, and co-evolving relationships between different components of human capital flows, CET theory asserts that "the rate and timing of one component within the system can be expected to differentially affect outcomes because other system components react" (Reilly et al., 2014, p. 772).

The aim of the present study is to better understand the effects of staffing events and contextual factors on work outcomes. We explore the way in which the magnitude of our hypothesized effects change over time. However, there is scant research on the temporal and dynamic effects of staffing events on unit work outcomes. This prevents us from developing complete formal hypotheses about these effects. However, by taking an exploratory approach in regards to temporal and dynamic effects of staffing events, we draw from the existing research to speculate about the way in which the unit response to staffing events may change over time and how the contextual factors considered in our study may affect the duration of these effects.

When a staffing event causes a change in the unit's human capital resources, other variables in the system are expected to change as well because the unit responds, absorbs the event's consequences over time, and adjusts accordingly. Staffing events, unit turnover rate, and unit performance may influence not only the current state of the system, but also cause changes to the system in the future. Moreover, depending on the strength and salience of each of these components and the context in which they take place, the nature and duration of these effects may differ.

Temporal effects of human capital inflow (hiring). In the discussion developing hypothesis 1, we explained that the arrival of new hires is expected to initially cause operational disruptions. This is because new hires and incumbents need time to adapt to the introduced change to the system. We expect this operational disruption to disappear gradually as both groups adjust to the new situation and the new ideas and energy of the newcomers starts to translate into an increase in unit performance. In evaluation of the temporal changes in the job satisfaction of newcomers, Boswell and her colleagues (2009) demonstrated that the new hires enjoy an initial increase in job satisfaction (honeymoon effect) but then their job satisfaction trends downward after a few months (hangover effect). Levels of job satisfaction eventually stabilize around a year after the arrival of the new employee. Bringing the results of this study up to the unit level, we expect that the initial operational disruptions, combined with high levels of job satisfaction among the new hires, will result in a decrease, no effect, or a small increase in initial unit performance. This depends on which effect (job satisfaction of the newcomers or the initial operational disruption) is stronger. After the initial period when both newcomers and incumbents adjust to the new situation, we expect the high levels of job satisfaction to become more pronounced. Therefore, we anticipate that the initial period is followed by an increase in job performance. This increase in job performance fades away or turns negative as the newcomers enter the hangover period. The hangover effect should gradually disappear as dissatisfied employees leave and the system stabilizes.

Our expectations about the temporal effects of hiring on turnover are informed by Jovanovic's (1979) matching model and Farber's (1994) empirical evaluation of the model. These studies showed that newcomers may join the unit without having enough actual information about whether they are a good fit to the unit or not. Thus, voluntary turnover rates are low immediately following their arrival because they are still gathering information about the job. As soon as newcomers realize the reality of their match to the job and the unit, an increase in voluntary turnover is expected as those who do not perceive a good fit decide to leave. After this phase is over, a secondary decrease in voluntary turnover rate is anticipated because those who did not find the unit a good match have already left and the remaining employees are less likely to turn over.

Temporal effects of human capital outflow (dismissal and layoff). As we discussed in the previous subsections, research strongly supports the notion that human capital outflow is generally associated with a decrease in unit performance, due to the operational disruptions and extra work burden added to the workload of the continuing employees. However, after employees operationally adjust to the change, we anticipate an increase in unit performance.

Employee dismissal is expected to improve unit performance over time when the initial adjustment phase after the dismissal of ‘bad apples’ who spoiled the barrel is over. Therefore, a gradual increase in unit performance and efficiency is predicted. Layoffs are usually planned to cut the costs associated with human capital and increase the unit performance.

As discussed in previous subsections, we anticipate a lower rate of voluntary turnover in the wake of dismissals (H2b) and a higher rate of turnover in response to layoffs (H3b). We explore the way in which the size and significance of these responses change over time.

Temporal effects of contextual factors. The relationship between staffing events and work outcomes is of practical importance to organizations that may be able to improve some aspects of the workplace context to reduce the negative effects of staffing events. We expect that positive internal contextual factors (i.e., higher levels of appreciation ritual participation and collective affective attitude) will shorten the time it takes for units to adjust to the changes introduced by staffing events. We expect more cohesive and positive units to adjust faster to recent staffing changes. In our temporal and dynamic analysis, we also explore the way in which the external context of local unemployment rate influences the size and duration of the effects of staffing events on work outcomes.

Informed by Reilly et al. (2014), we apply Panel Vector Auto Regression (PVAR) analysis to explore the temporal relationships in our model. We use the PVAR method to examine, in addition to the short-term analysis of our hypotheses, the co-evolution and mutual effects of HR-initiated staffing events, unit performance, and unit turnover rate on each other, over time and for different levels of contextual factors. As such, we evaluate whether our short-term hypotheses hold over time, considering mutual changes and interactions of the variables in the model.

3.3 Methods

3.3.1 Data and Setting

We used three datasets from a large national retailer whose stores (units) are located across the United States. The three datasets include financial performance, personnel data, and pulse survey responses for 1,849 stores from January 2014 through October 2015. Each store has an average of 95.78 employees (SD=39.50). Since we used data from a single organization, we were able to control for organizational policies and organization specific variables, such as industry characteristics, which are predictors of rate and frequency of staffing events (Shaw, 2011). In addition, we used unemployment data from the Bureau of Labor Statistics unemployment data for the metropolitan area in which each of the stores is located. Below we briefly introduce the three organizational datasets.

Financial dataset. The financial data include each store's monthly revenue and monthly targeted and actual EBITDA (Earnings Before Interest, Tax, Depreciation, and Amortization). EBITDA measures the operating performance of each store without factoring in financing, or accounting decisions, or store's tax environment. The financial data were, therefore, collected at the store-month level.

Personnel dataset. The personnel dataset is part of the organization's human resources actions and reasons reporting system. This indicates when each employee was hired and whether, when, and why the employee left his/her position. The HR system classifies turnover as either voluntary or involuntary. The details of this classification and reasons for voluntary and involuntary turnover are presented in Table 1. The personnel data therefore were available at the individual-day level. In our analysis, we aggregated the personnel data to the store-month level, the higher level of analysis at which the financial data are recorded.

Pulse survey dataset. This dataset is collected using a pulse survey that measures employee affective attitude, participation in the appreciation ritual, and team engagement. The survey has a few additional questions that are not discussed here because they are not relevant to the present study. Employees completed the pulse survey at the end of each day when they clocked out. Employees were not required to complete the survey. The system recorded all unanswered questions. The pulse survey answers were recorded at the individual-day level.

To ensure the quality of survey responses, the organization collected the pulse survey data anonymously. Therefore, we were not able to track the survey responses of individuals. The store ID is the only available identifier in the pulse survey data. We used pulse survey responses to find two indicators of stores' internal social and psychological workplace context (i.e., appreciation ritual participation and collective affective attitude). In our analysis, we aggregated the anonymous daily individual responses up to the store-day and then to the higher level of store-month at which the financial data are recorded.

In our sample, we only kept store-months that on average had at least a survey participation rate of 30%. With this criterion, 12 stores (0.006% of all stores in the sample) and 637 store-month observations (1.5% of our sample's store-months) were eliminated. The sample, therefore, includes 1,837 stores and 37,680 store-months. Average survey participation per store in our sample is 50% (SD=0.12).

3.3.2 Measures

Store financial performance. We used EBITDA margin as a measure of store's profitability by calculating log of EBITDA to revenue ratio. EBITDA margin is an index of financial performance of stores. It ranges from -64% to 24% in our data (Mean=0.00 and SD=9%).

Voluntary turnover rate. As mentioned above, personnel data provides information about when each employee started her/his job, and whether, when, and why s/he left the position. Using this data, for each store-month, we calculated the store-level voluntary turnover rate as the number of voluntary turnovers in a store within a given month relative to the average number of store employees in the same month.

Hiring rate. For each store-month, using the personnel data, we calculated the store-level hiring rate as the number of new-hires into a store within a given month relative to the average number of store employees in the same month.

Dismissal rate. For each store-month, using the personnel data, we calculated the store-level dismissal rate as the number of dismissals due to poor performance, lack of integrity, or violation of organizational rules and policies in a store within a given month relative to the average number of store employees in the same month.

Layoff rate. For each store-month, using the personnel data, we calculated the store-level layoff rate as the number of layoffs in a store within a given month relative to the average number of store employees in the same month. The layoff rate does not include the terminations of seasonal employees.

Appreciation ritual participation. About a decade ago, the HR department started an organization-wide daily appreciation ritual to improve employees' sense of gratitude, cohesion, and engagement. In this ritual, employees meet every day at the beginning of the day for about 10 minutes and begin by collectively repeating their mission out loud. Then, the store manager quickly reviews the store "numbers," mostly focusing on positive outcomes, and ends by providing some encouraging statements and guidelines. Actual examples of such encouraging words include:

- "We're doing great and we're in a pretty good shape this morning."

- “We just need to make sure our store is bright and clean, we’re smiling, greeting everyone.”
- “I want to thank everyone for the efforts they put forth.”
- “Our goal in member feedback is 80. Yesterday we were at 100. So, basically you could say we are perfect here, so, give yourself a hand of applause for that.”

Then the supervisor asks employees whether anyone wants to share any “focused recognition.” At this point, employees volunteer to share and recognize other employees’ positive contributions and prosocial behaviors. For example, in an actual appreciation meeting, an employee shared with the group:

> “This is what showing pride looks like to me. We are not responsible to assemble the products for customers here in store, but as soon as an elderly customer asked about assembling the product, Sally jumped in and very patiently explained the assembly process and showed the customer how to do it. The customer asked whether we can help her with assembling the product. Sally told the customer that she’ll put the product together for her and she can come back and pick it up.”

In response, other employees clapped for Sally. Typically, around four or five employees share their focused recognition each day. These meetings end with employees repeating a positive chant regarding how they, as a positive, motivated, and engaged team, are going to provide high quality service to customers. We have not shared the exact content of the mantra and have slightly changed the content of the appreciation experiences and names of the employees to protect the organization’s identity.

Although the general structure of the appreciation ritual is the same, store managers have the autonomy to customize the ritual as they see appropriate. We observed many different versions of this ritual across the sample of stores. In some of the stores managers and employees made the ritual a fun event by dancing and singing together. In the others, the manager and employees acted as if they were trying to cover the bare minimum. All of the morning shift employees who were present at the store attended the ritual, however employees who started later in the day were not exposed to the ritual. This fact makes the level of participation in the ritual exogeneous in that it varies based on the number of employees who happened to be present at the beginning of the morning shift.

Since November 2014, employees indicated whether they participated in the ritual in the clock-out survey. We aggregated this daily individual-level variable to a store-day level and then to a store-month level variable to develop an indicator of the strength of the appreciation ritual. To ensure the validity of the aggregation of individual-level responses to the store-day level, we examined ICC(1) and ICC(2) for a random day in the data. ICC(1) takes into account between-group variance and ICC(2) assesses the reliability of the group mean (Bliese, 2000). Together, these indices support aggregation of individual responses to operationalize collective appreciation ritual participation as a unit-level variable. The ANOVA was significant at $p<0.001$, indicating a significant difference in the appreciation ritual participation among the stores (ICC1= 0.05, ICC2=0.68, $p< 0.001$). Although ICC(1) reveals non-zero store variance, it is relatively small, a relatively small ICC(1) is common for group measures in organizations. For example, Hausknecht and Trevor (2009, p. 1071) reported ICC(1)s smaller than 0.06 for their group level measures, including group cohesion. They explained that relatively smaller ICC(1) values are “fairly typical of real-world data.”

Collective affective attitude. One of the questions on the pulse survey asked about employee affective attitude ("How did you feel at work today?"). Employees respond to the question using a five-point Faces Scale (Figure 1)[1]. We aggregated this daily individual-level variable first to the store-day level and then to the store-month level.

We consider this variable to be an indicator of store-level affective context. To ensure the validity of the aggregation of individual-level responses to store level, we calculated two types of intraclass correlation coefficient, ICC(1) and ICC(2), for a random day in the data. Together, these indices support the aggregation of individual responses to operationalize collective affective attitude. The ANOVA is significant at $p<0.001$, indicating a significant difference in the collective affective attitude among the stores (ICC(1)= 0.06, ICC(2)=0.86, $p< 0.001$).

Our single-item measure of employees' feelings at work is a proxy for general affective state and affective aspects of job satisfaction. While it does not measure affect at work comprehensively, the pulse survey made it possible to collect affective attitude data on a daily basis because it asked only one question. In the organizational behavior literature, affect at work is usually measured using a 20-item PANAs instrument or some

[1] Organizations have increasingly started to use similar items in pulse surveys (Haak, 2016; Mann & Harter, 2016). Advances in information technology has made it easier and less expensive for organizations to track, each day, employees' affective states, well-being, and job satisfaction at work. Some firms offer this service to track organizational climate data, on a daily basis (e.g., the Workmoods application). Long surveys with several items, when administered daily, are time-consuming and off-putting. Therefore, pulse surveys use one-item scales to save time and encourage steady participation. Since organizations are more often using these single-item Faces scales to measure affective states at work, it is necessary for the organizational behavior research to investigate the capacity of these items in predicting important work outcomes.

variation of it (Watson, Clark, & Tellegen, 1988). However, because there is a trade-off between length and frequency, researchers (especially in longitudinal studies), often use shorter PANAs scales due to concerns about the burden of repeatedly administering a long survey (Beal & Ghandour, 2011; Fuller et al., 2003; Kuppens, Van Mechelen, Nezlek, Dossche, & Timmermans, 2007; Russell, Weiss, & Mendelsohn, 1989).

To encourage frequent employee responses at clock-out, our pulse survey utilized face figures to represent different emotions (Figure 1). One of the most effective affect-based measures of job satisfaction (Brief & Weiss, 2002), this type of scale (usually referred to as the "Faces Scale"), was first introduced in the organizational behavior literature by Kunin (1955). Kunin believed that the Faces Scale could measure attitudes more accurately than verbal scales because the respondent would not have to translate their feelings into words. Several studies later provided further support for the construct validity of this scale (Dunham & Herman, 1975; Locke, Smith, Kendall, Hulin, & Miller, 1964).

Perceived unit engagement. In the first 3 months of 2015, the organization added another question to the pulse survey asking employees about the level of engagement in the store. ("Today, I was part of an engaged team"). Employees responded to this question using a five-point Likert scale ranged from 1 = strongly disagree to 5 = strongly agree. Since we do not have enough observation on this variable, we do not include it in our main analysis. We only use this variable in our supplementary analyses to evaluate whether our internal context variables increase the unit level engagement. We aggregated this daily individual-level variable first to the store-day level and then to the store-month level.

We consider this variable to be an indicator of store-level engagement and cohesion. To ensure the validity of the aggregation of individual-level responses to store level, we calculated two types of intraclass correlation coefficient, ICC(1) and ICC(2), for a random day in the data. Together, these indices support the aggregation of individual responses to operationalize cohesion and engagement in the stores. The ANOVA is significant at $p<0.001$, indicating a significant difference in the unit engagement among the stores (ICC(1)= 0.09, ICC(2)=0.74, $p< 0.001$).

Unemployment rate. The monthly unemployment rate for each store's corresponding metropolitan area was quantified by data obtained from the Bureau of Labor Statistics ("United States Department of Labor, Bureau of Labor Statistics," n.d.).

Year-month. We control for year-month effects. Due to the cyclical and seasonal nature of the retail industry, the time of the year influences organizational outcomes. Weather conditions, varying by season and month of the year, may also affect the store's customer traffic and outcomes. Because these effects are unrelated to our other independent variables, we used fixed-effect dummy codes to control for each year-month and exclude the effects of specific months on work outcomes.

Full-time/part-time ratio. We control for the effects of full-time/part-time ratio in stores on work outcomes. The personnel data include a dichotomous variable that shows whether each employee is full-time or part-time. Full-time employment in this organization is between 35-40 hours a week, while part-time employment is less than 35 hours a week. We aggregated this variable to store-month level to find the ratio of full-time to part-time employees.

Research has shown that full-time and part-time employees exhibit different job attitudes and work outcomes (Conway & Briner, 2002; D. C. Feldman, 1990) due to the nature of their relationship with the organization. Also, these two groups of employees have different costs and values for their organization. Therefore, we also took account of the ratio of full-time to part-time employees, since full-time and part-time employees could have different effects on work outcomes. Also, the nature of staffing decisions about part-time and full-time employees are different.

Seasonal turnover rate. We also control for the rate of seasonal turnover, which is a significant part of human capital flow in retail industry. We do not formally propose hypotheses for the effects of seasonal turnover rate on work outcomes, mainly because this event is highly specific to the retail industry.

Store format. We controlled for store formats to account for the idiosyncratic characteristics of various store formats in the organization. The products and departments within stores are very similar, but stores operate under slightly different formats.

3.3.3 Analytical Method[2]

In our panel data, monthly repeated measures are nested within stores. There are two principal sources of variance: variability between stores, and variability between months (within stores).

Cross-lagged analysis. When modeling variables that occur over time, it is important to take into account time-based dependencies such as autoregressive patterns in the data. We use Stata 14 to implement a test for serial correlation in the error terms of each equation in our model, as recommended by Wooldridge (2010). This test revealed that there is serial correlation in our dependent variables, in that we rejected the null hypothesis that there is no serial correlation in the equations ($p<0.00$). Therefore, to examine our hypotheses, we use a dynamic panel model that takes into account lags of the dependent variables and independent variables in the right-hand side (Figure 2). In particular, we use the cross-lagged panel model as presented in Figure 2. To implement the cross-lagged panel model, we use the Seemingly Unrelated Regression (SUR) equations system (Zellner, 1962) which allows us to investigate the effects in the dynamic panel data and accommodates the assumption that the dependent variables are interdependent. This method permits us to take into account the correlations between the error terms of the dependent variables and yields more efficient estimations than separate

[2] Since all the variables in the model are at the store-month level, we are not able to differentiate between events that happened in the beginning, middle, or end of the month. For example, if an employee joins on the last week of a month the performance for three weeks of that month was calculated without considering the effect of that new employee. On the other hand, if an employee joined on the first day of a month that month's performance includes the new employee's effect on performance. Since we are not able to differentiate between these different effects throughout the month, in our models we lag all independent variables to avoid the noise created by partial month employment movements.

OLS regressions. We do not include controls for store fixed effects because the context variables are virtually time-invariant characteristics of stores[3] and the inclusion of store fixed effects eliminates the context effects. However, to account for possible serial correlation and heteroskedasticity in our panel data, we cluster our data around stores and use the robust option (Call et al., 2015).

Moderation analysis. To evaluate moderation effects, we include the moderated regression procedures recommended in the literature (Aiken & West, 1991; Cohen, Cohen, West, & Aiken, 2003) in the SUR equations system. In other words, we include the interaction terms between staffing events and each context variable in the regressions that evaluate the link between staffing events and work outcomes. All the variables in the model are standardized. This facilitates the interpretation of the coefficients of the interaction terms and minimizes the multicollinearity problem (Aiken & West, 1991).

Dynamic analysis. To capture the dynamic nature of the relationships proposed in our hypotheses, we use a panel vector autoregressive (PVAR) model (for more details about the method see Holtz-Eakin, Newey, & Rosen, 1988; Reilly et al., 2014). In conducting the PVAR analysis, our analysis is informed by Reilly et al.'s (2014) work, where PVAR was used to examine the dynamic system of human capital flow and its impact on unit performance over time. The PVAR model, which is an extension of the VAR model for panel vector time series, is used when variables in the model are

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[3] To evaluate the stability of store-month context variables over time we calculated ICC(1) and ICC(2) for store-month affective attitude ($ICC(1)_{affective\ attitude}$=0.71, $ICC(2)_{affective\ attitude}$ =0.98, $p<0.001$), appreciation ritual participation ($ICC(1)_{appreciation\ ritual}$=0.67, $ICC(2)_{appreciation\ ritual}$=0.95, $p<0.001$), and unemployment rate($ICC(1)_{unemployment\ rate}$=0.81, $ICC(2)_{unemployment\ rate}$ =0.99, $p<0.001$)).

expected to be mutually endogenous, auto-correlated, and co-evolving over time. This model simultaneously estimates the relationship between its variables over time using several general methods of moments (GMM) equations (Enders, 2014; Reilly et al., 2014; Wooldridge, 2010).

As it uses impulse response functions (IRFs), PVAR also predicts how other variables in the model will change over time, in response to one standard deviation increase in one variable (Hamilton, 1994; Koop, Pesaran, & Potter, 1996; Pesaran & Shin, 1998). We use PVAR to understand how different staffing events, unit performance, and unit turnover mutually influence each other over time and at different levels of contextual variables.

To model IRFs, PVAR creates exogeneous shocks in each variable using Cholesky decomposition to rotate the error terms in a way that all error terms are orthogonal to each other. The Cholesky decomposition method decomposes the variance-covariance matrix of error terms into a lower triangular matrix (A) and its conjugate transpose. If we linearly transform the original error vector using A^{-1}, the resulting error by construction is orthogonal because its variance-covariance matrix is diagonal (Enders, 2014; I. Love & Zicchino, 2006). Under this condition, we can observe how a one standard deviation shock in only one variable in the system will impact other variables in the system over time. As such, impulse response functions trace "the impact of a shock in the variables of interest on the dependent variable one at a time" (Srithongrung & Kriz, 2014, p. 3). In other words, using the Cholesky decomposition, the program simulates shocks to the system and traces the effects of those shocks on endogenous variables.

To meet the identification requirements for Cholesky decomposition, we first followed existing theories to determine model specifications and the order in which variables were entered into the model in order to generate an identified model with orthogonal residuals for all the equations (I. Love & Zicchino, 2006). Without this ordering assumption the model would be underidentified. This order restricts the same-period effects of variables on one another and does not alter the way the trajectory of effects is determined. In other words, each variable can predict future values for all other variables, but in the same-period analysis, each variable predicts same-period values of only those variables that follow it in the order in which they were entered into the model. We consider the rate of layoffs as the most exogenous variable in our model. In other words, we assume that other variables do not have a contemporaneous effect on layoffs, because decisions about layoffs are well-calculated based on a unit's performance. Other staffing events or performance in the current month cannot change the layoff decisions in the same month. Dismissal decisions are entered into the model after layoffs, because these decisions are again usually rather long-term decisions and a function of individuals' previous poor performance. The next two variables that are entered into our model are hiring and voluntary turnover rates. It is more difficult to determine the order of these two variables in the model because it is theoretically conceivable that they may have contemporaneous effects on each other. Unit performance is the most endogenous variable in our model, because monthly financial performance is a function of all the events that happen in the store in that month. However, performance is calculated and announced in the following months, so it is unlikely to have a contemporaneous effect on staffing events. Another important factor that can help researchers determine the order in which variables should be entered into the model is the correlation between error terms of the time-series. According to Enders (2014), if the correlation between the error terms of two time-series is smaller than 0.2, the order of those variables does not change the restriction imposed on the model by Cholesky decomposition. In our data, all pairs of correlations among the error terms are smaller than 0.2, so the order in which variables were entered into the model is virtually irrelevant.

In the next step, we decide on the number of lags required in our model. We calculate the model selection measures for first- to fourth-order panel VARs in our model as instruments. Based on the three model selection criteria (MBIC, MAIC, MQIC) by Andrews and Lu (2001) and the overall coefficient of determination, third-order (three lagged) panel VAR was determined to be the preferred model, since it has the smallest MBIC (Modified Bayesian Information Criterion), MAIC (Marginal Akaike Information Criterion) and MQIC (Modified Quasi Information Criterion). These criteria are moment selection criteria for GMM estimation (for details see Andrews & Lu, 2001). It also minimizes Hansen’s J statistic which tests over-identifying restrictions (for details see Andrews & Lu, 2001). Therefore, based on the selection criteria demonstrated in Table 6, we decided to fit a third-order panel VAR model using GMM estimation.

Third, informed by existing research (Arellano & Bover, 1995; I. Love & Zicchino, 2006; Reilly et al., 2014) and in order to have unbiased coefficients, we apply Helmert transformation (a forward de-meaning method that demeans variables using means of future observations) on the variables in our model. This transformation results in unbiased coefficients, while preserving the lagged observations as instruments in the PVAR model (Arellano & Bover, 1995; I. Love & Zicchino, 2006; Reilly et al., 2014).

PVAR analysis allows us to forecast the strength and significance of the mutual effects of variables over 12 months. We conduct 2000 Monte Carlo simulations to generate 90% confidence intervals for these effects (I. Love & Zicchino, 2006).

3.4 Results

The within-stores, between-stores, and overall descriptive statistics are presented in Table 2. Except for performance, all variables are standardized, but the numbers reported in Table 2 are variable summaries before standardization of the variables. Table 3 shows both the within-stores (below diagonal) and between-stores (above diagonal) intercorrelations among the study variables.

3.4.1 Cross-lagged Results

Table 4[4] presents the results of the cross-lagged model (Figure 2) and contains replications of the equation predicting unit performance without (Model 1) and with the context moderators (Models 2, 3, and 4, participation in appreciation ritual, collective affective attitude, and local unemployment rate, respectively). Table 5 presents replications of the equation predicting unit voluntary turnover rate without (Model 1) and with the context moderators (Models 2, 3, and 4).

[4] In Tables 4 and 5, we present the results of the simultaneous cross-lagged analysis only for unit performance (Table 4) and unit voluntary turnover rate (Table 5). Results of other equations are available upon request.

Model 1 (Table 4) demonstrates that staffing events, whether HR-initiated or employee-initiated (voluntary turnover), are linked to store performance. More specifically, one standard deviation increase in hiring rate corresponds to 0.02% increase in unit performance in the subsequent month. This finding indicates a relationship that is in the opposite direction to what we predicted in Hypothesis 1a (H1a). One possible explanation is that it takes newcomers less than a month to learn about the details of their job and other unit members do not need to spend a full month to bring them up to speed. On the other hand, newcomers bring fresh energy, knowledge, and skills to the organization. They also have higher job satisfaction and are more motivated to exert effort in the first few months in the new job (honeymoon effect) (Boswell, Boudreau, & Tichy, 2005; Boswell et al., 2009). As such, we observe an increase in unit performance in the subsequent month after an increase in hiring rate. We also found that one standard deviation increase in employee dismissal rate and layoff rate are linked to 0.01% decrease in unit performance in the subsequent month, supporting hypotheses H2a and H3a ($\beta_{\textit{Employee}\text{ dismissal rate-Unit performance}}=-0.01$, $p<0.05$; $\beta_{\textit{Layoff rate-Unit performance}}=-0.01$, $p<0.001$). This result suggests that HR-initiated staffing events of termination and layoff, perhaps in contrast to their intended effect on performance, are linked to a decrease in unit performance. Also, in support of Hypothesis H4a, our results show that one standard deviation increase in unit voluntary turnover rate is associated with 0.02% decrease in unit performance in the subsequent month ($\beta_{\textit{Voluntary turnover rate-Unit performance}}=-0.02$, $p<0.001$).

Model 1 (Table 5) portrays the relationship between hiring rate and unit voluntary turnover rate in the subsequent month. It demonstrates that one standard deviation increase in the former corresponds to 0.18 standard deviation increase in the latter, providing support for hypothesis H1b ($\beta_{\textit{Hiring rate-Voluntary turnover rate}}=0.18$, $p<0.001$). However, results for Model 1 do not support a relationship between employee dismissal rate or layoff rate and unit voluntary turnover rate in the subsequent month. Therefore, Hypotheses H2b and H3b were not supported. In supporting hypothesis H4b, results for Model 1 show that one standard deviation increase in voluntary turnover rate corresponds to 0.19 standard deviation increase in voluntary turnover rate in the subsequent month ($\beta_{\textit{Voluntary turnover rate -Voluntary turnover rate}}=0.19$, $p<0.001$).

As shown in Table 4, we could not find any support for a direct relationship between any of the internal context variables (participation in appreciation ritual and collective affective attitude) and store performance. Therefore, H5a and H6a were not supported. While we could not find a link between store performance and the context variables, a relationship between voluntary turnover rate and the context variables was observed. Table 5 shows that participation in appreciation rituals (Model 2), collective affective attitude (Model 3), and unemployment rate (Model 4) are all negatively linked to unit voluntary turnover rate. More specifically, the results show that one standard deviation increase in appreciation ritual participation or in collective affective attitude corresponds to 0.06 standard deviation decrease in voluntary turnover rate (H5b and H6b). This suggests that units that are more exposed to appreciation rituals and have a more positive affective attitude benefit from lower rates of voluntary turnover ($\beta_{\textit{Appreciation}}$

$_{\textit{ritual participation}\text{-Voluntary turnover rate}}=0.06$, p<0.001; $\beta_{\textit{Collective}\text{ affective attitude-Voluntary turnover }\textit{rate}}=0.06$, p<0.001). We also found that a one standard deviation increase in the unemployment rate in the metropolitan area where the store is located is linked to 0.09 standard deviation decrease in voluntary turnover rate (H7). This suggests that rates of voluntary turnover are lower in areas where job opportunities are more limited ($\beta_{\textit{Unemployment}\text{ rate-Voluntary turnover rate}}=0.09$, p<0.001). Thus, H5b, H6b, and H7 were supported, demonstrating that context variables have direct relationships with unit turnover rate.

3.4.2 Moderation Results

The moderation hypotheses (H8, H9, and H10) were tested using the moderated regression procedures recommended by existing studies in the literature (Aiken & West, 1991; Cohen et al., 2003). We included the interaction terms between staffing events and context variables in the SUR equations system. Results are displayed in Models 2, 3, and 4 of Table 4 and Table 5.

Model 2 in Table 4 and Model 2 in Table 5 do not provide support for the moderating effects of appreciation ritual participation on the relationship between staffing events and work outcomes. Therefore, H8 was not supported. We also did not find support for the moderating effects of collective affective attitude on the link between staffing events and unit performance, or on the links between dismissal and layoff rates and voluntary turnover rate. The only part of H9 that was supported is the mitigating effect of collective affective attitude on the relationship between hiring rate and voluntary turnover rate in the subsequent month. More specifically, Model 3 in Table 5 shows that the interaction term between hiring rate and collective affective attitude is negatively associated with voluntary turnover rate in the subsequent month, supporting H9e ($\beta_{Hiring \times \text{Collective affective attitude-Voluntary turnover}}$ =-0.02, p<0.001). This suggests that collective affective attitude makes the positive relationship between hiring rate and voluntary turnover rate less pronounced. This result supports our hypothesis that the context of positive affective mitigates the negative consequences of hiring on unit voluntary turnover rate.

Finally, we find support for hypotheses 10a, 10b, and 10d. Model 4 in Table 5 reveals that the interaction terms between hiring rate and unemployment rate, dismissal rate and unemployment rate, and voluntary turnover rate and unemployment rate are negatively associated with voluntary turnover rate in the subsequent month ($\beta_{Hiring \times Unemployment\ rate\text{-}Voluntary\ turnover}$ =-0.02, p<0.01; $\beta_{Dismissal \times Unemployment\ rate\text{-}Voluntary\ turnover}$ =-0.01, p<0.01; $\beta_{\text{Voluntary turnover} \times \text{Unemployment rate-Voluntary turnover}}$ =-0.02, p<0.05). This demonstrates that the context of a poor local labor market mitigates the increase in voluntary turnover rate in the subsequent month due to hiring and voluntary turnover. Also, it shows that a poor labor market context enhances the decrease in voluntary turnover rate in the subsequent month due to employee dismissals.

3.4.3 Dynamic Results

Next, we examine our model through a dynamic lens using Panel Vector Auto Regression (PVAR). This method allows us to treat all variables in the model as endogenously determined. Table 7 demonstrates the coefficients from the GMM equations in the PVAR model. This table presents the effects of lagged variables on unit performance and voluntary turnover rate. Impulse response functions are calculated to measure the isolated effect of each of the variables. In other words, using the Cholesky decomposition, the program simulates shocks to the system and traces the effects of those shocks on endogenous variables over time. The impulse responses for the model without the moderating effects of the context variables are illustrated in Table 8[5] and Figure 2 (effects of shocks on unit performance) and Figure 3 (effects of shocks on voluntary turnover rate).

The results in Table 8 show that one standard deviation increase in the hiring rate (controlling for its effect on other variables and their mutual effects on each other over time), increases unit performance in the first month (honey-moon effect) and then decreases it slightly in the second month. The decrease in performance becomes the largest in the third month following the hire (perhaps this is the peak of hang-over effect). Performance gradually increases in the following month. A similar shock to hiring rate increases voluntary turnover rate significantly and the effect gradually disappears in 4 months.

Table 8 also demonstrates that a one standard deviation increase in the employee dismissal rate decreases unit performance in the first month after the shock, but this effect turns positive in the next two months and then it fades away. A similar shock to the rate of employee dismissal decreases unit voluntary turnover rate in the following month. This effect diminishes after a month and fades away in the third month after the shock.

[5] The effects fade away after 6 months. Therefore, we only include the changes over subsequent 6 months. We only present the results relevant to our hypotheses (effects of shock in staffing events on unit performance and voluntary turnover rate in the subsequent months). The effects on other variables in the model are available upon request.

Based on the results shown in Table 8, we observe that one standard deviation increase in the rate of layoffs does not have a significant effect on unit performance. The effect, however, appears in month 3 following the shock, where we see a significant increase in unit performance, but this effect disappears in the subsequent months. A similar shock to the layoff rate increases unit voluntary turnover rate in the first and third months after the shock. One explanation as to why we do not observe a significant response to layoff is perhaps due to the very low base rate of this event in this specific organization. When it comes to downsizing, the organization we chose to study typically decided to close an entire store rather than laying off a number of employees within a particular store. Among the 37,680 store-month observations in our data set, only 1,703 store-months have a none-zero layoff rate.

Finally, results shown in Table 8 and Figure 3 indicate that a one standard deviation increase in voluntary turnover rate decreases unit performance in the month following the shock. The magnitude of the decrease shrinks in the subsequent month to grow again in the opposite direction, as it increases unit performance in the third month following the shock. The effect fades away in the fourth month. Table 8 and Figure 4 also show a steady increase in voluntary turnover rate in the three months following a shock in voluntary turnover rate. This increase peaks in the third month after the shock and the magnitude of the effect slowly decreases in the following months.

To evaluate the moderating effects of the context variables on unit performance and voluntary turnover over time, first we divided the data into two categories of high (top 40%) and low (bottom 40%) in each of the context variables[6]. Then, we ran PVAR analysis on the two categories. For example, for analysis of collective affective attitude, we divided the data into the two categories of high in collective attitude and low in collective attitude, ran PVAR on each of the two categories, and compared them. Results for moderating effects of the context variables (i.e., appreciation ritual, collective affective attitude, and local unemployment rate) are presented in Tables 9, 10, and 11, and Figures 5 through 10.

Table 9 and Figures 5 and 6 present the changes in unit performance and voluntary turnover rate over time in two distinguished contexts where participation in appreciation ritual is either high or low. Results show that when participation in appreciation ritual is high, one standard deviation increase in dismissal rate improves performance after 2 months. But the same shock decreases unit performance and the effect disappears in 2 months, when participation in appreciation rituals is low.

A one standard deviation increase in layoffs decreases unit performance in the following 3 months after the shock in low participating stores, but the effect is insignificant for high participating stores.

When participation in appreciation ritual is high, a one standard deviation increase in voluntary turnover rate decreases unit performance in the next 6 months and the effect

[6] We decide on the top and bottom 40% of the observations to create the high and low categories, because we do not want to miss much data. It is especially important, because our PVAR analysis requires three lags for each current observation.

gradually fades away. However, when participation in appreciation ritual is low, we observe a larger decrease in unit performance which disappears after 3 months.

When the rate of participation in appreciation ritual is low, we observe a steady increase in the rate of voluntary turnover in the three months following a shock in voluntary turnover rate. The effect disappears afterwards. On the other hand, when the rate of participation in appreciation ritual is high, in response to the same shock, the magnitude of increase in voluntary turnover rate drastically shrinks after the first month and disappears afterwards.

A one standard deviation increase in dismissal rate creates a steady decrease in voluntary turnover rate which gradually fades away in the 6 months after the shock. The same shock does not have a significant effect on voluntary turnover rate when the rate of participation in appreciation ritual is low.

Table 10 depicts the changes in unit performance and voluntary turnover rate in response to different staffing events in two distinguished contexts where collective affective attitude is either high or low. Results show that regardless of whether collective affective attitude is high or low, one standard deviation increase in hiring rate drives similar patterns of unit performance over time. However, the same shock has a more pronounced effect on increases of voluntary turnover rate in stores that have lower collective affective attitude. As expected, the increase in voluntary turnover rate in response to hiring is smaller and disappears faster (in 3 months versus 5 months) in stores with high levels of collective affective attitude. Moreover, in stores with high levels of collective affective attitude, a one standard deviation increase in hiring leads to a decrease in voluntary turnover rate 5 months after the shock. In stores that have lower collective affective attitude, the increase in hiring rate increases voluntary turnover rate and the effect disappears after 5 months. In other words, we do not observe an eventual decrease in voluntary turnover rate for these stores in response to an increase in hiring rate.

Table 10 also shows that in stores with higher levels of collective affective attitude, a one standard deviation increase in employee dismissal rate decreases performance in the first month after the shock to a lesser extent than stores with lower levels of collective affective attitude. Further into the future, we observe similar patterns of change in performance in both groups. In stores with higher collective affective attitude compared to stores with lower collective attitude, we observe a greater decrease in voluntary turnover rate in response to a one standard deviation increase in employee dismissal. In stores with high collective affective attitude, there is a diminishing decrease in voluntary turnover that fades away after 4 months. In stores with low collective affective attitude, this diminishing decrease in voluntary turnover disappears after 2 months.

A one standard deviation increase in layoff has a small positive effect on unit performance in the first month for both low and high categories of collective affective attitude. However, this effect disappears in the second month after layoff for stores with high levels of collective affective attitude. This effect grows for stores with low levels of collective attitude for another two months and then it fades away. We do not observe significant differences in response to layoff in terms of voluntary turnover rate between the two groups.

Table 10 also shows that a one standard deviation increase in voluntary turnover rate has a stronger negative effect on unit performance in the first month in stores with higher levels of collective affective attitude. Afterwards, we observe a strong increase in performance for 3 months in stores with lower levels of collective attitude. This increase is much less pronounced in stores with high levels of collective affective attitude and disappears a month earlier.

Finally, voluntary turnover rate in subsequent months in response to increase in voluntary turnover rate grows slowly and with the same rate in the first 2 months following the shock for stores with high or low collective affective attitude. While we observe a peak in voluntary turnover rate in the third month for stores with low collective affective attitude, we see a sharp decrease in voluntary turnover rate for stores with high collective affective attitude. While the effect of the shock on voluntary turnover rate disappears eventually for stores with high collective affective attitude, the same effect remains significant even 6 months following the shock for stores with low collective affective attitude.

Table 11 illustrates the changes in unit performance and voluntary turnover rate in response to different staffing events in two distinguished contexts where the local unemployment rate is either low or high. Results show that when local unemployment rate is high, a one standard deviation increase in hiring rate increases unit performance in the first month after the shock to a greater extent than when the local unemployment rate is low. In the second month the effects of an increase in hiring results in decrease in performance, but still the size of decrease is smaller in stores that have higher local unemployment rates. This pattern does not hold in the subsequent months. The same shock to hiring rates increases voluntary turnover rate to a greater extent in stores with lower levels of local unemployment in the first month after the increase in hiring rate. Afterwards, the pattern of response to hiring rate becomes virtually identical for the two categories of high and low unemployment. As expected, the increase in voluntary turnover rate in the subsequent month in response to a shock in voluntary turnover rate is smaller for stores where local unemployment rate is higher. This pattern is observed only in the first month after the shock. We do not observe significantly different patterns of response in terms of unit performance and voluntary turnover rate to other staffing events among stores with high or low levels of local unemployment.

3.4.4 Supplementary Analyses

In developing our hypotheses, we drew on the studies that hold that collective appreciation and collective affective tone positively impact work outcomes as they build cohesion and increase engagement. We tested this relationship by running a series of cross-lagged analyses evaluating the mutual link between appreciation ritual participation, collective affective attitude, and unit engagement. The results of these analyses are demonstrated in Table 12. Results support that exposure to the appreciation ritual has positive effects on both perceived unit engagement and collective affective attitude in the subsequent month. Model 1 in Table 12 shows that a one standard deviation increase in participation in the appreciation ritual increases perceived unit engagement by 0.06 standard deviation (β *Ritual* participation-perceived unit engagement =0.06, $p<0.001$). Model 3 in Table 12 demonstrates that a one standard deviation increase in participation in the appreciation ritual increases collective affective attitude by 0.07 standard deviation (β *Ritual participation-Collective* affective attitude =0.07, $p<0.001$). Likewise, according to Model 2 in Table 12 collective affective attitude is shown to improve unit engagement, such that a one standard deviation increase in collective affective attitude increases perceived unit engagement by 0.20 standard deviation (β *Collective* affective attitude-perceived unit engagement =0.20, $p<0.001$)

3.5 Discussion

Staffing decisions and subsequent staffing events influence work outcomes within the workplace context. Much remains to be examined about the tripartite relationship of staffing events-workplace context-work outcome. Blending the human capital resources and workplace context theories, we developed a dynamic model that provides insights to the relationship between human capital flow and workplace performance. Moreover, these results demonstrate how contextual factors—both internal and external to the workplace—modify these relationships over time.

We used longitudinal personnel, financial, and pulse survey data collected from 1,837 stores of a large national retailer to empirically evaluate our model. Our assessment offers several major contributions. We provide some support for the notion that staffing events impact subsequent unit performance and voluntary turnover rates. However, these effects do not develop analogously over time and also differ under varied contextual situations.

3.5.1 Implications for Theory and Research

We put in conversation several theoretical accounts in the literature on strategic human resource management and organizational behavior to build our theoretical argument regarding the dynamic staffing events-context-outcomes relationships. We draw from CET theory (Nyberg & Ployhart, 2013) to explain the co-evolving relationship between different components of human capital flow and unit performance while accounting for the internal and external context against which these relationships unfold over time. We appeal to EST (Morgeson et al., 2015) to explain the dynamic nature of staffing events and how their overall strength and effect on other components of the system change as a function of their novelty, the level of disruption they cause in the status-quo, and their criticality.

We also provide evidence in support of Fehr et al.'s (2017) theoretical framework that argues for collective appreciation as a result of consistent participation in appreciation programs and rituals in the workplace. Participation in appreciation rituals in our data set is an exogeneous variable, because only employees who happened to be present in the store at the opening time attended the ritual. This exogeneous variation in exposure to the ritual gave us a unique opportunity to evaluate the effects of formal appreciation programs on collective outcomes. Our results demonstrate that participation in the formal appreciation rituals decreases voluntary turnover rate, perhaps through the creation of a more cohesive and positive context and increased employee job embeddedness.

We build upon the theoretical works of George (1990) and Knight et al. (2018) to conceptualize collective affective attitude. We find that units with higher levels of collective affective attitude have lower rates of turnover. Thus, we conclude that a positive and engaging environment can help to retain employees. We also show that a positive collective affective attitude can facilitate newcomer socialization and adjustment. In stores with a more positive collective affective attitude, the increase in voluntary turnover rate in response to hiring is significantly lower.

In addition to using cross-lagged analysis to examine the short-term relationships between staffing events and work outcomes, we apply a more precise methodological approach to evaluation of the dynamic and systemic aspects of our theoretical model. Reilly et al. (2014) have explained that static models, and even longitudinal models with time lags, may not be able to fully evaluate the complex and dynamic nature of human capital flow. They have pointed out that the PVAR analysis, rarely used in the field of management, is uniquely apt to examine these relationships. This analytical approach advances our knowledge of human capital flow because it permits us to follow simulated exogeneous shocks in each component of the model and observe the nature and duration of changes in other components.

Our empirical results also contribute to the literature by validating and extending prior findings in several ways. Notably, we show that human capital inflow generally improves unit performance in the first month after the corresponding staffing event (honeymoon effect) and decreases unit performance in the following months (hangover effect).

We also show that human capital outflow commonly decreases unit performance in the first month following the corresponding staffing event. In the subsequent months, different levels of increase or no increase in performance are observed, depending on the type of human capital loss. Our analysis partially supports the claim that favorable internal context mitigates the initial decrease in performance caused by human capital loss. This is perhaps because in more positive and cohesive contexts, employees tend to share resources and collaborate to compensate for the loss of human capital.

When it comes to the relationship between staffing events and voluntary turnover rate, our results demonstrate that contextual factors, whether internal or external to the workplace, strongly affect unit turnover rates. While favorable internal context decreases voluntary turnover, perhaps by creating more cohesive units and making employees more embedded in their jobs (Felps et al., 2009; Mitchell et al., 2001), higher unemployment rates persuade employees not to leave their jobs, perhaps due to limited alternative opportunities in the labor market (Trevor, 2001).

Our results also support the conclusions of previous studies (Farber, 1994; Jovanovic, 1979; Kammeyer-Mueller & Wanberg, 2003) by showing that human capital inflow increases unit voluntary turnover for the first few months following the arrival of newcomers. Our findings expand upon the existing research by demonstrating that favorable internal context abates the increase in voluntary turnover rates due to human capital inflow. This effect is observed perhaps because the more positive and cohesive the unit, the more capably it accommodates the newcomers. As a result, it is more likely that the newcomers feel that they fit in with their new job and the unit, hence keeping the rates of voluntary turnover low.

Our research also partially supports the notion that favorable contexts boost and prolong the decrease in voluntary turnover rates brought about by employee dismissal. We show that favorable contexts can mitigate and shorten the increase in voluntary turnover rate in the months following layoffs.

3.5.2 Implications for Practice

In practice, organizations actively hire employees with the hope that the new talent will enhance unit level performance. However, the continued success of this staffing practice depends on the organization's ongoing ability to integrate new members (Argote & Ingram, 2000; Rink et al., 2013). The question becomes whether the workplace context supports the smooth integration of new members. Employee dismissals and layoffs are sometimes required, as layoffs have become an integral part of organizational life (Datta, Guthrie, Basuil, & Pandey, 2010). The Bureau of Labor Statistics has reported over 30 million employee layoffs between 1994 and 2010 (Davis et al., 2015). The survival of organizations relies on their ability to mitigate the negative effects of human capital outflow on the employees who remain behind.

Given the effects they have on key organizational outcomes, the consequences of staffing events are of enormous practical importance. Because these events can disrupt work outcomes (Hausknecht et al., 2009), organizations seek to manage and mitigate the effects of these events on survivors. Our research answers the question of whether organizations can rely on a supportive context to achieve this goal. More specifically, we provide some support that organizations can mitigate the consequences of staffing events by improving internal workplace context. Appreciation rituals or similar collective positive interventions that promote positive affective attitude, team cohesion, and prosocial behaviors can help reduce the negative consequences of staffing events.

3.5.3 Limitations and Directions for Future Studies

This research includes several limitations that should be addressed. First, our data and empirical approach make our results generalizable to the retail sector or other occupations in which replacement of human capital requires minimal preparation and training (broadly corresponding to low task complexity occupations in the O*NET job zone of one or two (e.g., cashiers, retail sales staff) that require relatively low preparation and training. Our results regarding the integration of newcomers and their effect on unit performance suggest that the adjustment of newcomers in these types of occupations may take less than a month. However, our study does not provide a clear picture as to how the adjustment of new hires, or a unit's response to human capital loss might be different in occupations with different levels of complexity and employee interdependence. Therefore, one direction for future research would be examining our model for other occupations in different industries where tasks are typically more complex and interdependent and the transfer of knowledge to new employees requires more time and resources.

Second limitation of this study is that we were not able to evaluate the quality of human capital flow into or out of the units. One of the important contributions of CET theory is its emphasize on both quantity and quality of human capital flow in understanding the consequences of the employee movements. As such, future studies should also take into consideration the quality of the human capital gain or loss in understanding the consequences of staffing events on workplace outcomes.

Third, we did not use a validated instrument to measure the positive and negative affect separately. The affect data are collected using a single-item Faces Scale asking employees about how they feel at work. While it is reasonable to initially focus on more generalized affect, especially because of the growing interest in collecting this type of data in organizations, it will be useful to differentiate between positive and negative affects in order to more fully understand the affective context of the workplace. Existing research has shown that positive and negative affectivities have distinct attitudinal, behavioral, and performance outcomes at the individual level (Frijda, 1986; Keltner & Haidt, 1999) and it would be informative to examine these relationships at the unit level and investigate whether the distinct collective positive and negative affects can differentially modify the relationship between staffing events and work outcomes. Also, it may be of interest to research in strategic HR management to measure collective gratitude or affective attitude with referent shift, so that the survey questions ask about the collective sense of gratitude or affective tone in the workplace. This referent shift makes the measured construct by these questions more in line with the literature of organization climate.

Finally, another limitation of this study is that our data only include monthly financial performance measures at the store level. This measure of performance is informative and has been widely used in the literature (Hale, Ployhart, & Shepherd, 2016; McElroy et al., 2001; Shaw et al., 2005). However, it is more distal to behavioral reactions to staffing events or contextual factors. One fruitful future direction would be to use behavioral measures of performance such as customer service quality.

3.6 Figures

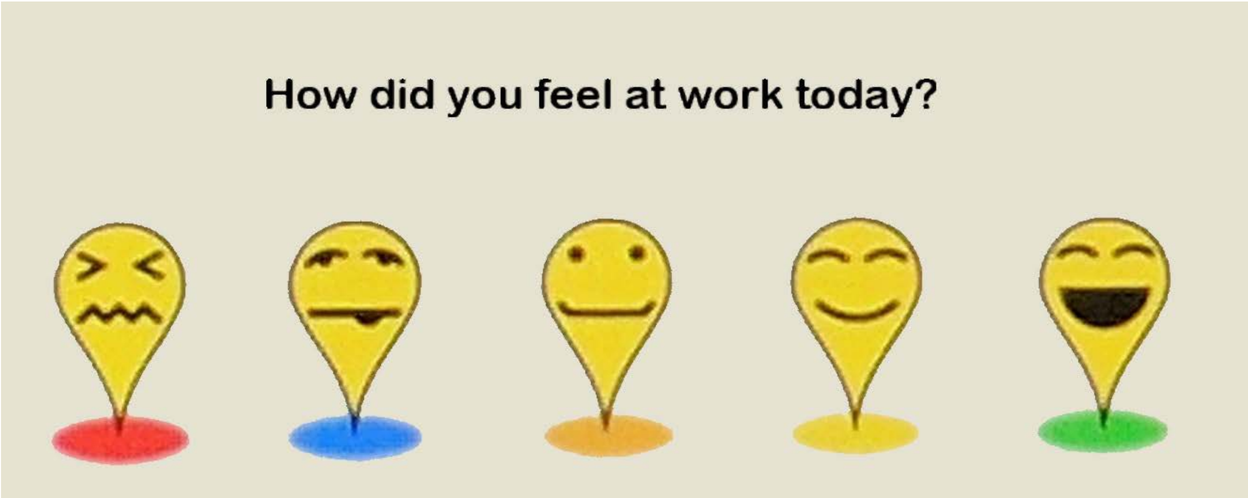

Figure 3-1 Affect question in the pulse-survey

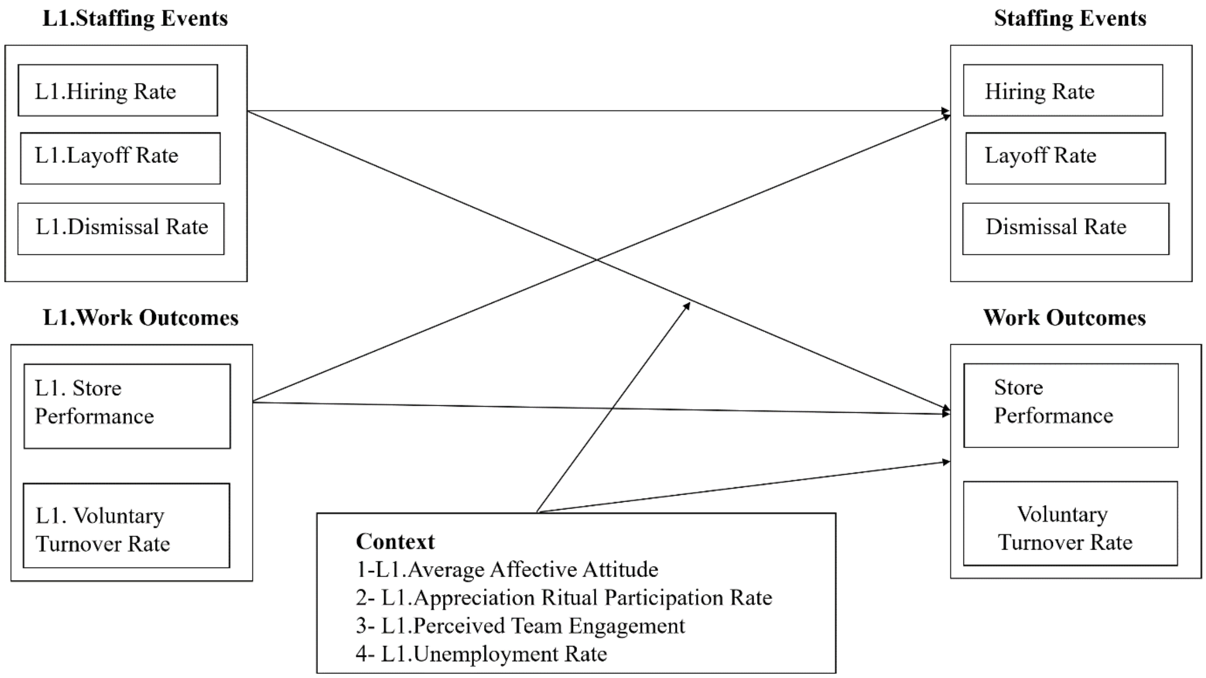

Figure 3-2 Study Model[7]

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[7] L1. Stands for one month lag in the variable

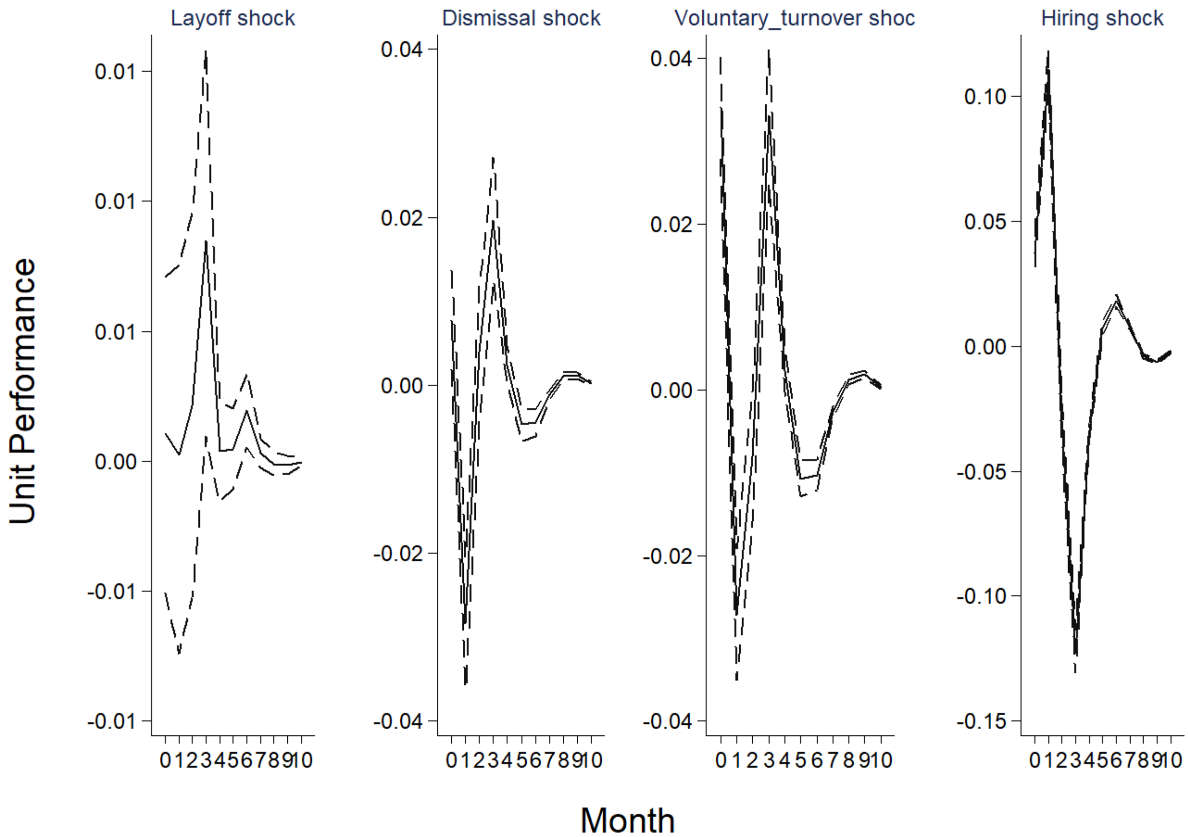

Figure 3-3 Unit performance impulse response to shocks to model variables over months

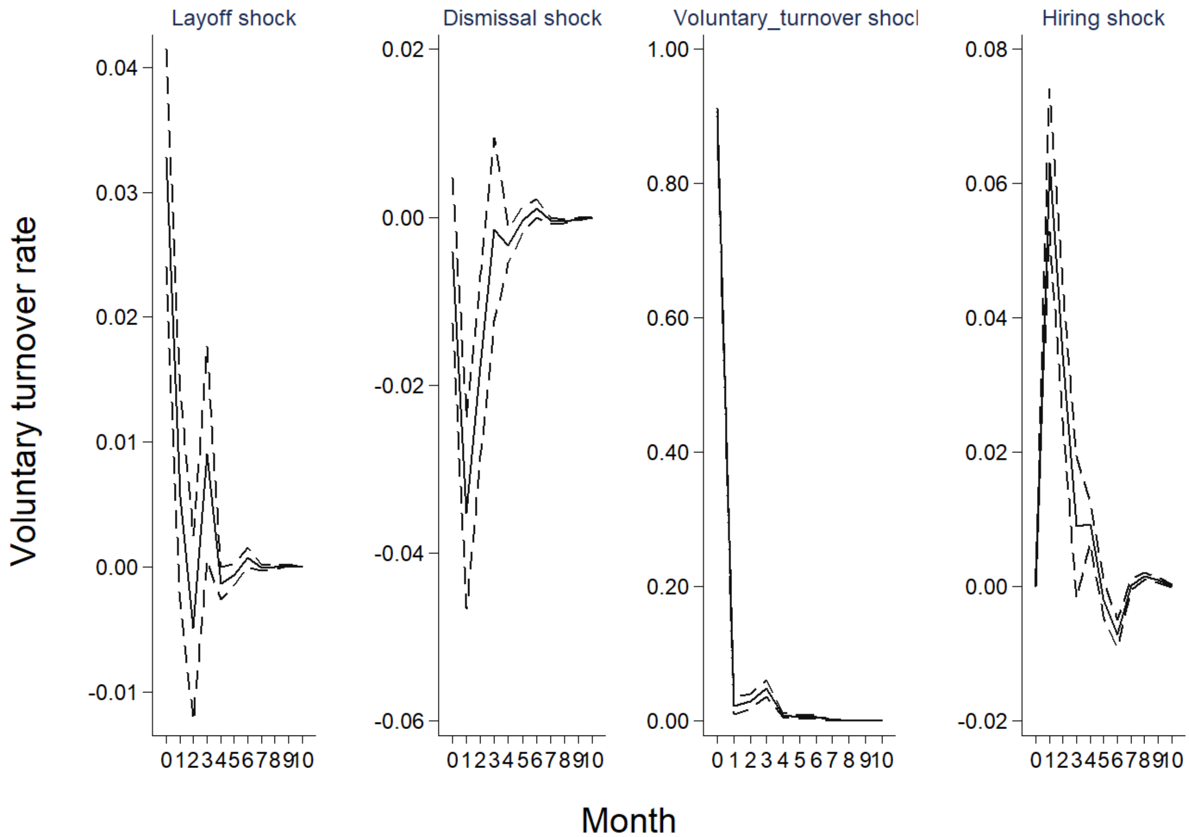

Figure 3-4 Unit turnover rate impulse response to shocks to model variables over months

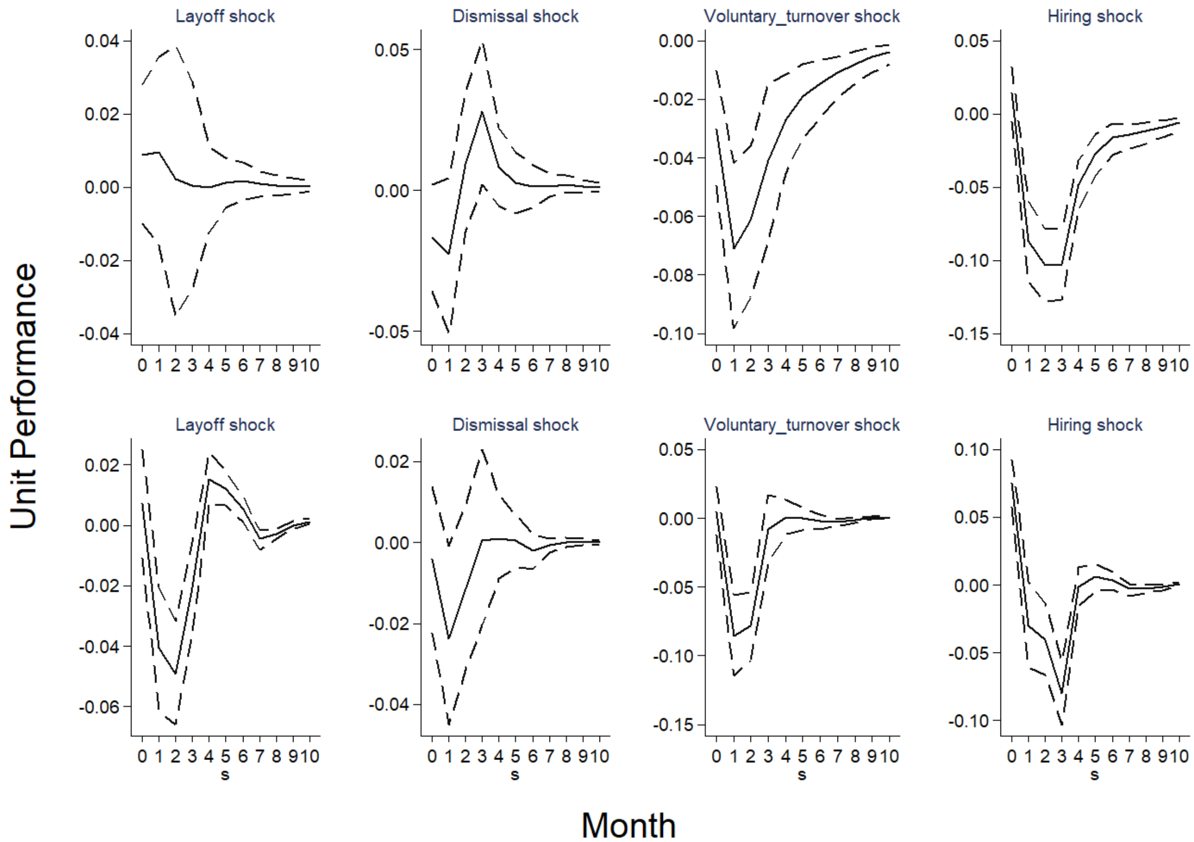

Figure 3-5 Unit performance impulse response to shocks to model variables over months. Top panel, top 40% of appreciation ritual participation; Bottom panel, bottom 40% of appreciation ritual participation

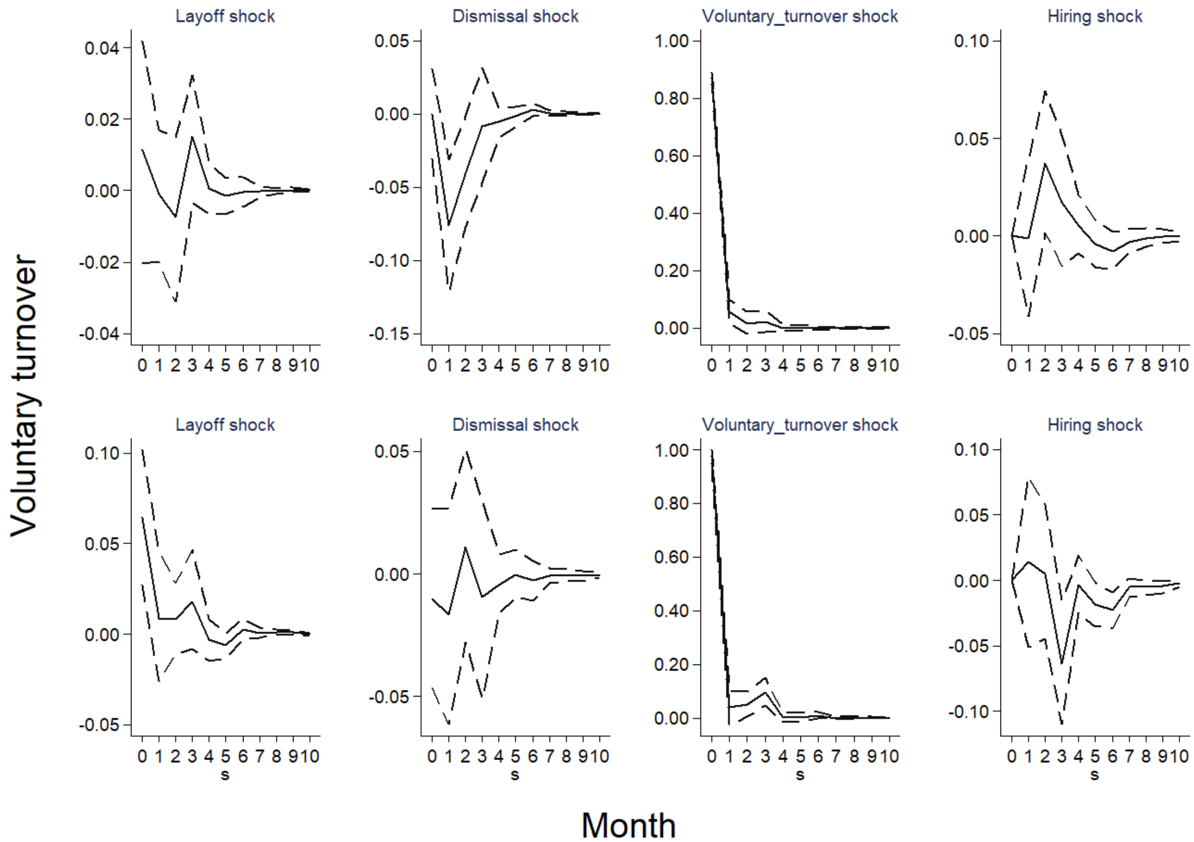

Figure 3-6 Unit voluntary turnover impulse response to shocks to model variables over months. Top panel, top 40% of appreciation ritual participation; Bottom panel, bottom 40% of appreciation ritual participation

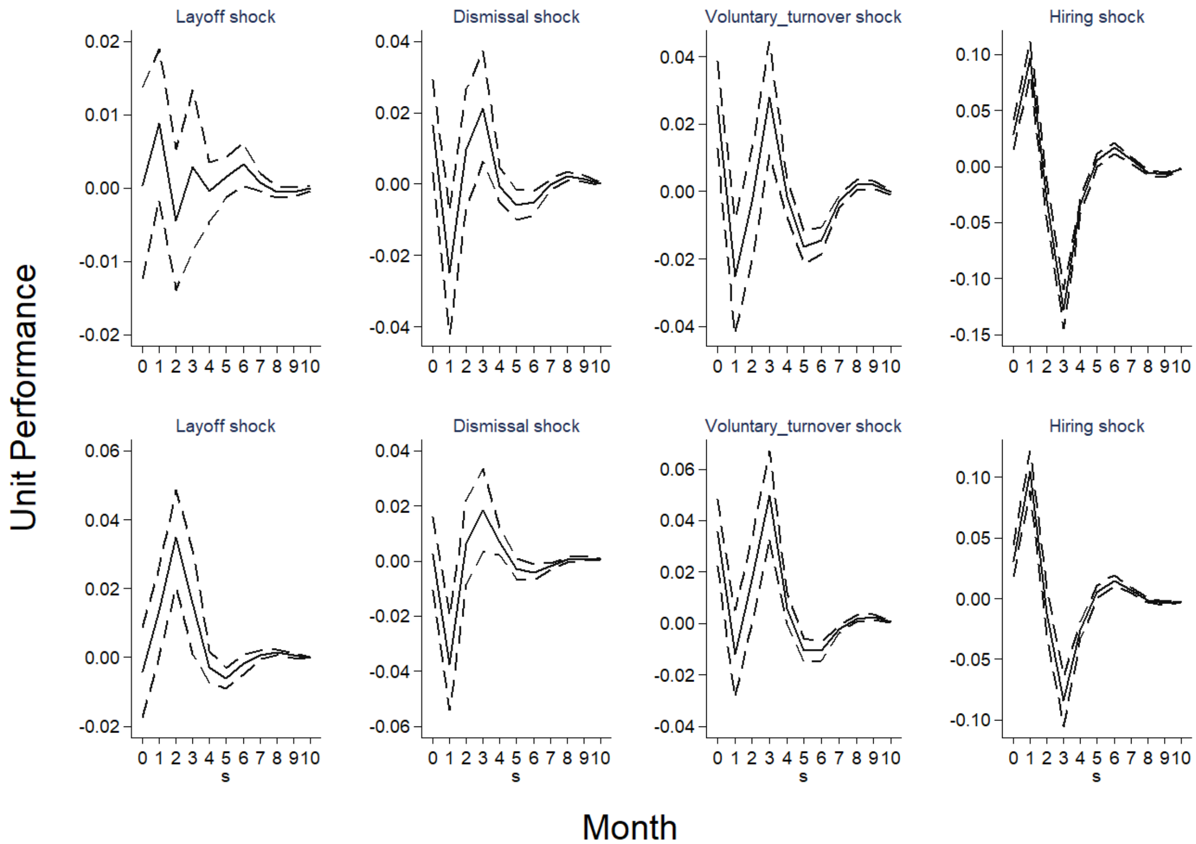

Figure 3-7 Unit performance impulse response to shocks to model variables over months. Top panel, top 40% of collective affective attitude; Bottom panel, bottom 40% of collective affective attitude

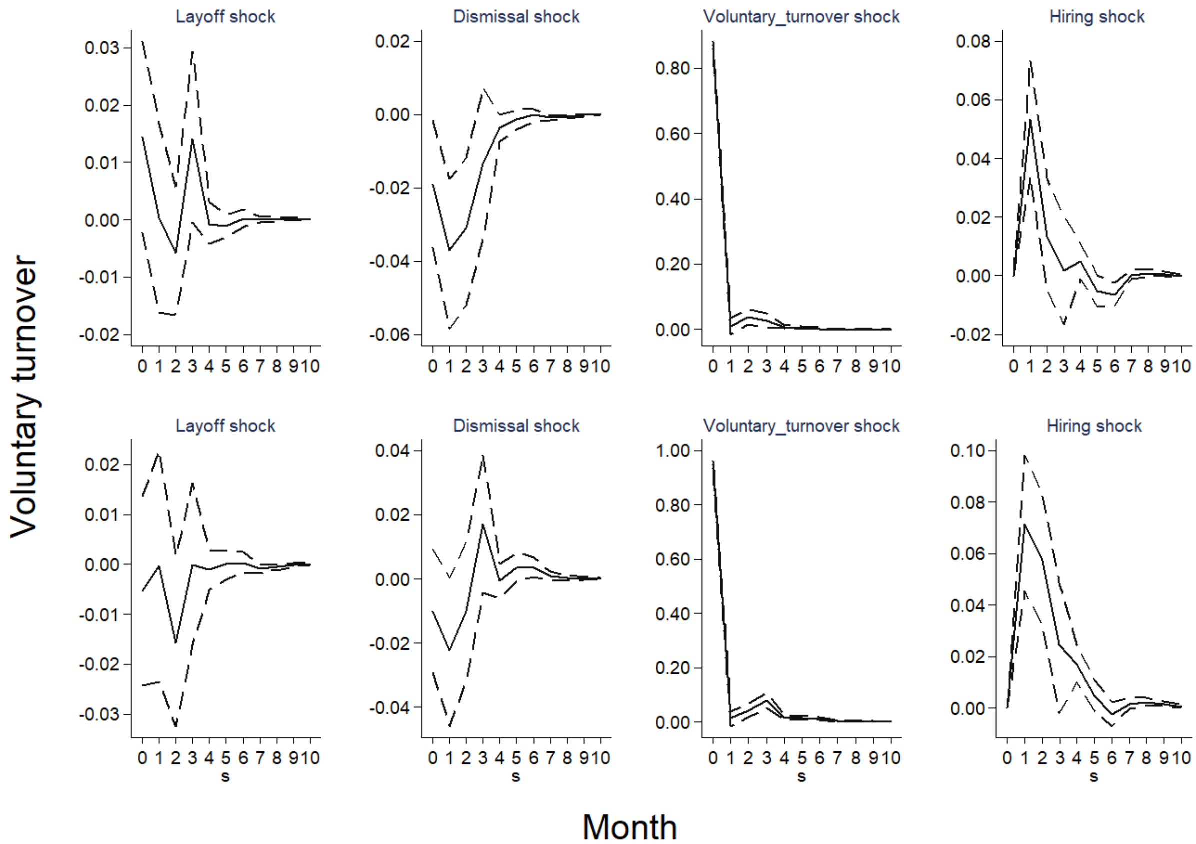

Figure 3-8 Unit voluntary turnover impulse response to shocks to model variables over months. Top panel, top 40% of collective affective attitude; Bottom panel, bottom 40% of collective affective attitude

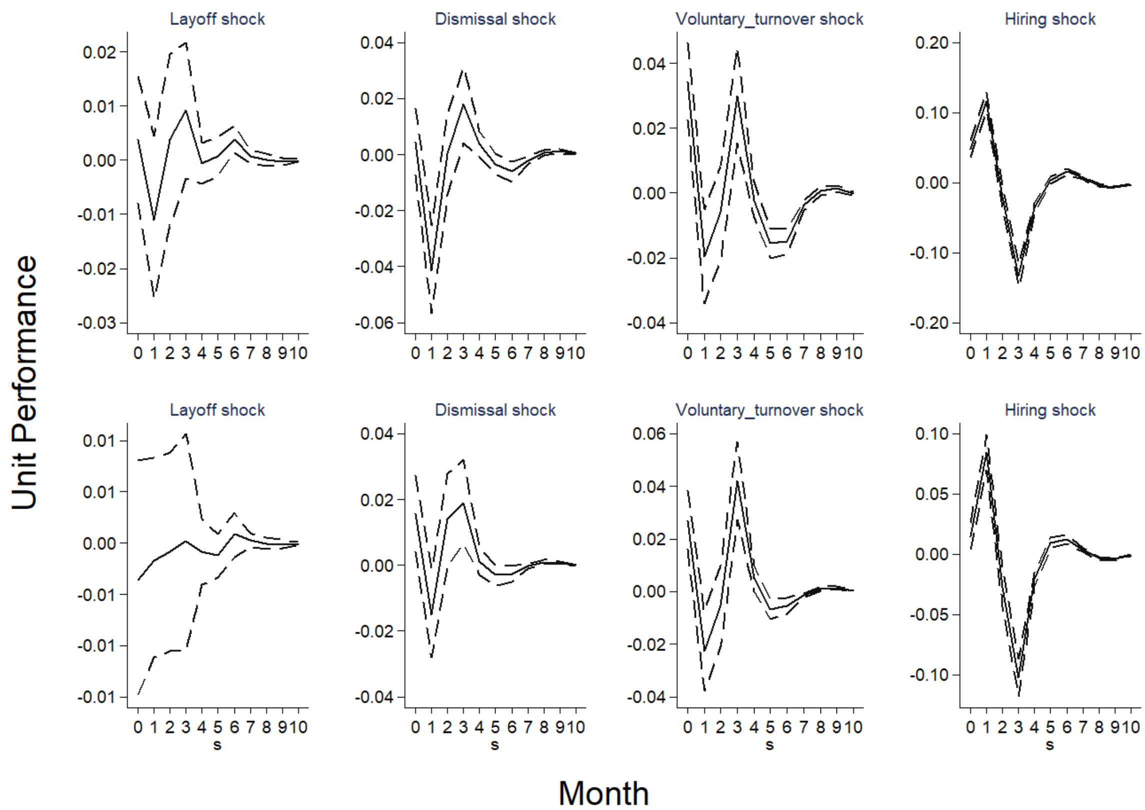

Figure 3-9 Unit performance impulse response to shocks to model variables over months. Top panel, top 40% of unemployment rate; Bottom panel, bottom 40% of unemployment

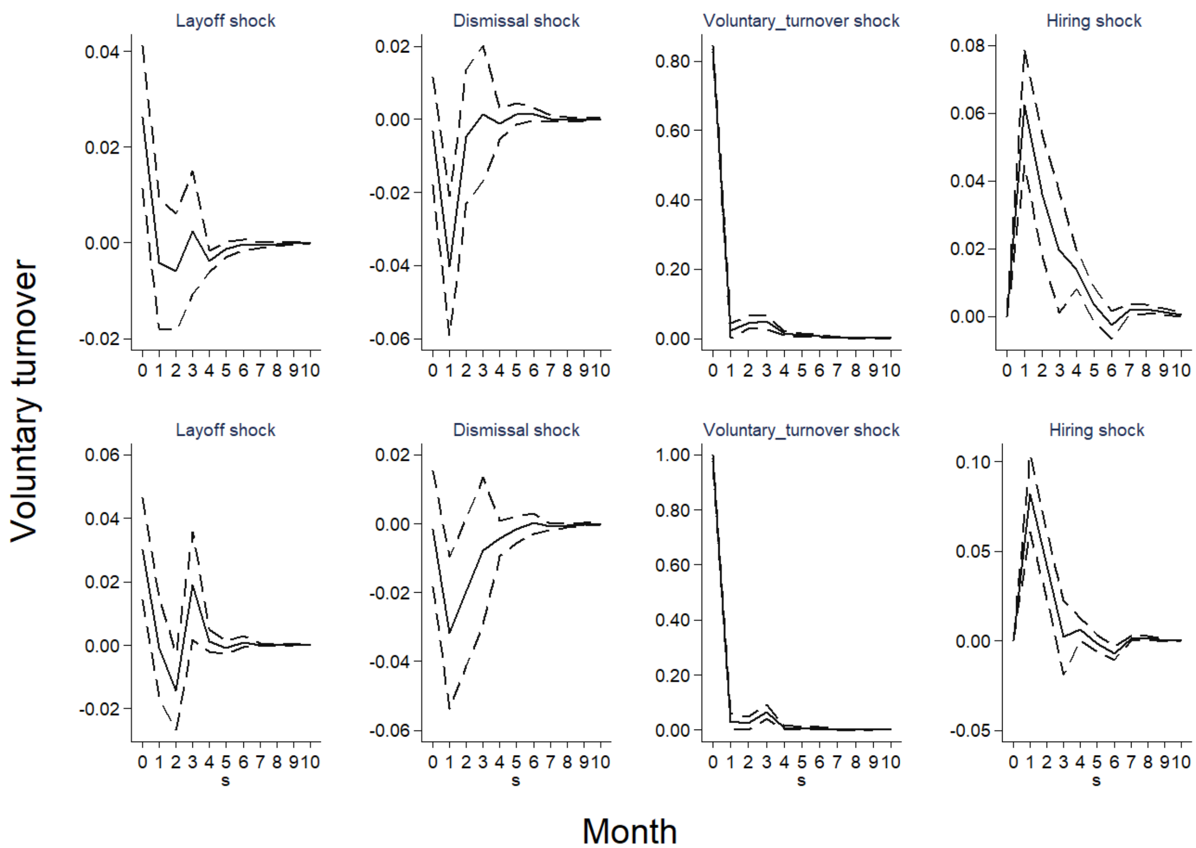

Figure 3-10 Unit voluntary turnover impulse response to shocks to model variables over months. Top panel, top 40% of unemployment rate; Bottom panel, bottom 40% of unemployment rate

3.7 Tables

Table 3-1 Types of Turnover

Type of Turnover	Reason	Frequency	% in type	% of total turnover
Involuntary-Dismissal	Attendance	13,337	28.22	0.05
Involuntary-Dismissal	Integrity	10,100	21.37	0.04
Involuntary-Dismissal	Violation of Rules and Policies	9,117	19.29	0.03
Involuntary-Dismissal	Poor Performance	8,218	17.39	0.03
Involuntary-Layoff	Staff Reduction - Position Elimination	6,485	13.72	0.02
Voluntary Turnover	Personal Reasons	73,111	31.94	0.26
Voluntary Turnover	Job Abandonment	66,659	29.12	0.24
Voluntary Turnover	Career Advancement	34,145	14.92	0.12
Voluntary Turnover	Return to school	17,292	7.55	0.06
Voluntary Turnover	Compensation/Benefits	7,649	3.34	0.03
Voluntary Turnover	Retirement, Voluntary	5,989	2.62	0.02
Voluntary Turnover	Health Reasons	5,149	2.25	0.02
Voluntary Turnover	Dissatisfied w/Type of Work	5,123	2.24	0.02
Voluntary Turnover	Dissatisfied with Hours	4,626	2.02	0.02
Voluntary Turnover	Other reasons	4,334	1.89	0.02
Voluntary Turnover	Dissatisfied with Location	2,537	1.11	0.01
Voluntary Turnover	Management	811	0.35	0.00
Voluntary Turnover	Company Strategy/Vision/Future	752	0.33	0.00
Voluntary Turnover	Learning and Development	712	0.31	0.00

Note. Percent in type column shows among those who (in)voluntarily turned over what percent left for the reason mentioned in the row.
Percent of total turnover shows what share of all terminated employees left for the reason mentioned in the row.

Table 3-2 Descriptive Statistics

Variable		N	Mean	SD	Min	Max
Unit performance	overall	37,680	0.00	0.09	-0.62	0.24
	between			0.05	-0.37	0.22
	within			0.07	-0.64	0.35
Unit voluntary turnover rate	overall	37,680	0.06	0.04	0.00	0.35
	between			0.02	0.01	0.14
	within			0.03	-0.06	0.31
Appreciation ritual participation	overall	16,870	0.82	0.10	0.32	1.00
	between			0.09	0.37	0.99
	within			0.06	0.52	1.07
Collective affective attitude	overall	34,082	4.04	0.30	1.97	4.95
	between			0.26	2.43	4.79
	within			0.16	2.68	4.97
Unemployment rate	overall	37,680	0.06	0.02	0.01	0.29
	between			0.02	0.02	0.24
	within			0.01	0.00	0.16
Unit hiring rate	overall	37,680	0.04	0.04	0.00	0.33
	between			0.01	0.00	0.10
	within			0.04	-0.06	0.30
Unit dismissal rate	overall	37,680	0.01	0.01	0.00	0.22
	between			0.01	0.00	0.05
	within			0.01	-0.04	0.17
Unit layoff rate	overall	37,680	0.00	0.00	0.00	0.22
	between			0.00	0.00	0.01
	within			0.00	-0.01	0.21

Note. Number of stores=1,837.
Missing values in Collective affective attitude due to low survey participation
Missing values in Appreciation ritual participation is because this question was
Added to the pulse survey later in November 2014.

Table 3-3 Within-Store and Between-Store Intercorrelations between Study Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unit performance		0.00	-0.03	0.02	-0.19	0.00	0.02	-0.01
Unit voluntary turnover rate	-0.04		0.04	-0.07	-0.05	0.00	-0.02	0.06
Appreciation ritual participation	0.02	-0.19		0.09	-0.06	-0.01	-0.02	0.01
Collective affective attitude	0.01	-0.13	0.35		0.07	-0.08	0.01	-0.01
Unemployment rate	0.00	-0.13	-0.12	0.06		-0.18	0.00	-0.02
Unit hiring rate	-0.01	0.72	-0.12	-0.04	-0.06		-0.01	-0.03
Unit dismissal rate	-0.06	0.21	0.02	0.03	-0.02	0.42		0.01
Unit layoff rate	-0.08	0.04	-0.01	-0.05	0.06	0.03	0.06	

Note. Correlation values greater than 0.05 are significant at $p<0.05$.
Correlations below the diagonal are between unit correlations (n=1,837 stores).
Correlations above the diagonal are the within-unit correlations over 4 to 22 months (mean=21.15, SD=2.55).

Table 3-4 SUR model predicting unit performance without and with moderators

	(1)	(2)	(3)	(4)
L.Unit performance	0.52^{***}	0.60^{***}	0.51^{***}	0.52^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
L.Voluntary turnover rate	-0.02^{***}	-0.02^{***}	-0.02^{***}	-0.02^{***}
	(0.00)	(0.01)	(0.00)	(0.00)
L.Appreciation ritual participation		-0.02		
		(0.01)		
L.Affective attitude			0.01	
			(0.01)	
L.Unemployment rate				0.01
				(0.01)
L.Hiring rate	0.02^{***}	0.00	0.02^{***}	0.02^{***}
	(0.00)	(0.01)	(0.00)	(0.00)
L.Dismissal rate	-0.01^{*}	-0.00	-0.01^{*}	-0.01^{*}
	(0.00)	(0.01)	(0.00)	(0.00)
L.Layoff rate	-0.01^{***}	-0.01^{*}	-0.01^{***}	-0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
L.Appreciation ritual participation × L.Voluntary turnover rate		-0.01^{**}		
		(0.00)		
L.Appreciation ritual participation × L.Hiring rate		-0.00		
		(0.01)		
L.Appreciation ritual participation × L.Dismissal rate		-0.00		
		(0.01)		
L.Appreciation ritual participation × L.Layoff rate		0.00		
		(0.00)		
L.Affective attitude × L.Voluntary turnover rate			0.00	
			(0.00)	
L.Affective attitude × L.Hiring rate			-0.01^{**}	
			(0.00)	
L.Affective attitude × L.Dismissal rate			0.00	
			(0.00)	
L.Affective attitude × L.Layoff rate			-0.00	
			(0.00)	
L.Unemployment rate × L.Voluntary turnover rate				0.00
				(0.00)
L.Unemployment rate × L.Hiring rate				0.00
				(0.00)
L.Unemployment rate × L.Dismissal rate				0.00
				(0.00)

L.Unemployment rate × L.Layoff rate				0.00
				(0.00)
Control variables	Yes	Yes	Yes	Yes
Observations	35,528	15,112	32,441	35,528

Note. In model (1) no moderator is included. In model (2) moderator is appreciation ritual participation, in model (3) moderator is collective affective attitude, and in model (4) the moderator is unemployment rate. L. stands for lagged, representing one month lagged variable. Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3-5 SUR model predicting unit voluntary turnover rate without and with moderators

	(1)	(2)	(3)	(4)
L.Unit performance	0.01	-0.02	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
L.Voluntary turnover rate	0.19***	0.18***	0.19***	0.17***
	(0.01)	(0.01)	(0.01)	(0.01)
L.Appreciation ritual participation		-0.06***		
		(0.01)		
L.Collective affective attitude			-0.06***	
			(0.01)	
L.Unemployment rate				-0.09***
				(0.01)
L.Hiring rate	0.18***	0.17***	0.18***	0.16***
	(0.00)	(0.01)	(0.01)	(0.01)
L.Dismissal rate	0.00	0.01	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
L.Layoff rate	0.01	0.01	0.00	0.00
	(0.00)	(0.01)	(0.01)	(0.01)
L.Appreciation ritual participation × L.Voluntary turnover rate		0.00		
		(0.01)		
L.Appreciation ritual participation × L.Hiring rate		0.01		
		(0.01)		
L.Appreciation ritual participation × L.Dismissal rate		0.01		
		(0.01)		
L.Appreciation ritual participation × L.Layoff rate		0.00		
		(0.01)		
L.Affective attitude × L.Voluntary turnover rate			0.01	
			(0.01)	
L.Affective attitude × L.Hiring rate			-0.02***	
			(0.01)	
L.Affective attitude × L.Dismissal rate			-0.00	
			(0.01)	
L.Affective attitude × L.Layoff rate			-0.00	
			(0.01)	
L.Unemployment rate × L.Voluntary turnover rate				-0.02*
				(0.01)
L.Unemployment rate × L.Hiring rate				-0.02**
				(0.01)
L.Unemployment rate × L.Dismissal rate				-0.01**
				(0.01)

L.Unemployment rate × L.Layoff rate				0.00
				(0.01)
Control variables	Yes	Yes	Yes	Yes
Observations	35,528	15,112	32,441	35,528

Note. In model (1) no moderator is included. In model (2) moderator is appreciation ritual participation, in model (3) moderator is collective affective attitude, and in model (4) the moderator is unemployment rate. L. stands for lagged, representing one month lagged variable. Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3-6 Tests to determine the order of PVAR model

lag	CD	J	J-pvalue	MBIC	MAIC	MQIC
1	0.98	3965.81	0.00	2461.15	3671.81	3282.00
2	0.99	2452.22	0.00	1449.12	2256.22	1996.35
3	0.99	841.13	0.00	339.58	743.13	613.19

Table 3-7 GMM Results for Impact of Each Lagged System Variable on Other System Variables

	Unit performance			Voluntary turnover rate		
Independent variables	b	se	t	b	se	t
L.Layoff	0.00	0.00	1.12	0.01	0.01	1.35
L.Dismissal	-0.03	0.01	-5.35	-0.04	0.01	-4.84
L.Voluntary turnover	-0.03	0.01	-5.80	0.03	0.01	3.15
L.Hiring	0.11	0.00	23.09	0.07	0.01	9.80
L.Performance	0.13	0.01	13.54	-0.01	0.01	-1.21
L2.Layoff	0.00	0.00	0.58	0.00	0.00	-0.95
L2.Dismissal	0.00	0.00	0.91	-0.02	0.01	-2.58
L2.Voluntary turnover	-0.01	0.00	-2.51	0.03	0.01	3.47
L2.Hiring	-0.05	0.01	-9.53	0.03	0.01	4.73
L2.Performance	-0.03	0.01	-4.59	0.00	0.01	0.29
L3.Layoff	0.00	0.00	0.67	0.01	0.01	1.64
L3.Dismissal	0.01	0.00	3.05	0.00	0.01	-0.18
L3.Voluntary turnover	0.03	0.00	6.35	0.04	0.01	5.11
L3.Hiring	-0.11	0.01	-20.53	0.00	0.01	0.71
L3.Performance	-0.08	0.01	-13.45	0.07	0.01	9.13

Note. variables are lagged three months. The order of variables in this table is according to the order in which they entered the PVAR model.

Table 3-8 The Effects of Staffing Events on Work Outcomes Over Time

Dependent	Shock	Month1	Month2	Month3	Month4	Month5	Month6
Performance	Layoff	0 (-.01 to .01)	0 (-.01 to .01)	.01 (0 to .02)	0 (0 to 0)	0 (0 to 0)	0 (0 to 0)
Performance	Dismissal	-.03 (-.04 to -.02)	0 (0 to .01)	.02 (.01 to .03)	0 (0 to 0)	0 (-.01 to 0)	0 (-.01 to 0)
Performance	Voluntary turnover	-.03 (-.04 to -.02)	-.01 (-.02 to 0)	.03 (.02 to .04)	0 (0 to 0)	-.01 (-.01 to -.01)	-.01 (-.01 to -.01)
Performance	Hiring	.11 (.1 to .12)	-.03 (-.04 to -.02)	-.12 (-.13 to -.11)	-.03 (-.04 to -.03)	.01 (0 to .01)	.02 (.02 to .02)
Voluntary turnover	Layoff	.01 (0 to .01)	0 (-.01 to 0)	.01 (0 to .02)	0 (0 to 0)	0 (0 to 0)	0 (0 to 0)
Voluntary turnover	Dismissal	-.04 (-.05 to -.02)	-.02 (-.03 to -.01)	0 (-.01 to .01)	0 (-.01 to 0)	0 (0 to 0)	0 (0 to 0)
Voluntary turnover	Voluntary turnover	.02 (.01 to .03)	.03 (.02 to .04)	.05 (.04 to .06)	.01 (.01 to .01)	.01 (0 to .01)	.01 (0 to .01)
Voluntary turnover	Hiring	.06 (.05 to .07)	.03 (.02 to .04)	.01 (0 to .02)	.01 (.01 to .01)	0 (0 to 0)	-.01 (-.01 to -.01)

Note. Impulse responses Over Time to Shocks to the Variables in the Shock Column. Months 7 through 12 are omitted, because the effects decline to zero.

Table 3-9 Moderating Effects of Appreciation Ritual Participation on the Relationship between Staffing Events and Work Outcomes Over Time

Dependent	Shock	Level	Month1	Month2	Month3	Month4	Month5	Month6
Performance	Layoff	High	.01 (-.02 to .04)	0 (-.04 to .04)	0 (-.03 to .03)	0 (-.01 to .01)	0 (-.01 to .01)	0 (0 to .01)
Performance	Layoff	Low	-.04 (-.06 to -.02)	-.05 (-.07 to -.03)	-.02 (-.04 to -.01)	.02 (.01 to .02)	.01 (.01 to .02)	.01 (0 to .01)
Performance	Dismissal	High	-.02 (-.05 to 0)	.01 (-.02 to .03)	.03 (0 to .05)	.01 (-.01 to .02)	0 (-.01 to .01)	0 (-.01 to .01)
Performance	Dismissal	Low	-.02 (-.05 to 0)	-.01 (-.03 to .01)	0 (-.02 to .02)	0 (-.01 to .01)	0 (-.01 to .01)	0 (-.01 to 0)
Performance	Voluntary turnover	High	-.07 (-.1 to -.04)	-.06 (-.09 to -.04)	-.04 (-.07 to -.01)	-.03 (-.05 to -.01)	-.02 (-.03 to -.01)	-.01 (-.03 to -.01)
Performance	Voluntary turnover	Low	-.09 (-.11 to -.06)	-.08 (-.1 to -.05)	-.01 (-.03 to .02)	0 (-.01 to .01)	0 (-.01 to .01)	0 (-.01 to 0)
Performance	Hiring	High	-.09 (-.12 to -.06)	-.1 (-.13 to -.08)	-.1 (-.13 to -.08)	-.05 (-.07 to -.03)	-.03 (-.04 to -.01)	-.02 (-.03 to -.01)
Performance	Hiring	Low	-.03 (-.06 to 0)	-.04 (-.06 to -.01)	-.08 (-.1 to -.06)	0 (-.02 to .01)	.01 (0 to .02)	0 (0 to .01)
Voluntary turnover	Layoff	High	0 (-.02 to .02)	-.01 (-.03 to .01)	.02 (0 to .03)	0 (-.01 to .01)	0 (-.01 to 0)	0 (0 to 0)
Voluntary turnover	Layoff	Low	.01 (-.03 to .04)	.01 (-.01 to .03)	.02 (-.01 to .05)	0 (-.01 to .01)	-.01 (-.01 to 0)	0 (0 to .01)
Voluntary turnover	Dismissal	High	-.08 (-.12 to -.03)	-.04 (-.08 to 0)	-.01 (-.05 to .03)	-.01 (-.02 to 0)	0 (-.01 to 0)	0 (0 to .01)
Voluntary turnover	Dismissal	Low	-.02 (-.06 to .02)	.01 (-.03 to .05)	-.01 (-.05 to .03)	0 (-.02 to .01)	0 (-.01 to .01)	0 (-.01 to .01)
Voluntary turnover	Voluntary turnover	High	.06 (.02 to .1)	.02 (-.02 to .06)	.02 (-.01 to .06)	0 (-.01 to .01)	0 (-.01 to .01)	0 (-.01 to .01)
Voluntary turnover	Voluntary turnover	Low	.04 (-.02 to .1)	.05 (.01 to .1)	.1 (.05 to .15)	0 (-.02 to .02)	0 (-.01 to .02)	.01 (0 to .02)
Voluntary turnover	Hiring	High	0 (-.04 to .04)	.04 (0 to .07)	.02 (-.02 to .05)	.01 (-.01 to .02)	0 (-.02 to .01)	-.01 (-.02 to 0)
Voluntary turnover	Hiring	Low	.01 (-.05 to .08)	.01 (-.05 to .06)	-.06 (-.11 to -.02)	0 (-.03 to .02)	-.02 (-.04 to 0)	-.02 (-.04 to -.01)

Note. Impulse responses over time to shocks to the variables in the shock column for bottom 40% of appreciation ritual participation (Level=Low) and top 40% of appreciation ritual participation (Level=High).
months 7 through 12 are omitted, because the effects decline to zero.

Table 3-10 Moderating Effects of Collective Affective Attitude on the Relationship between Staffing Events and Work Outcomes Over Time

Dependent	Shock	Level	Month1	Month2	Month3	Month4	Month5	Month6
Performance	Layoff	High	.01 (0 to .02)	0 (-.01 to .01)	0 (-.01 to .01)	0 (0 to 0)	0 (0 to 0)	0 (0 to .01)
Performance	Layoff	Low	.01 (0 to .03)	.03 (.02 to .05)	.02 (0 to .03)	0 (-.01 to 0)	-.01 (-.01 to 0)	0 (0 to 0)
Performance	Dismissal	High	-.02 (-.04 to -.01)	.01 (-.01 to .03)	.02 (.01 to .04)	0 (-.01 to 0)	-.01 (-.01 to 0)	-.01 (-.01 to 0)
Performance	Dismissal	Low	-.04 (-.05 to -.02)	.01 (-.01 to .02)	.02 (0 to .03)	.01 (0 to .01)	0 (-.01 to 0)	0 (-.01 to 0)
Performance	Voluntary turnover	High	-.03 (-.04 to -.01)	0 (-.02 to .01)	.03 (.01 to .04)	0 (-.01 to 0)	-.02 (-.02 to -.01)	-.01 (-.02 to -.01)
Performance	Voluntary turnover	Low	-.01 (-.03 to 0)	.02 (0 to .03)	.05 (.03 to .07)	.01 (0 to .01)	-.01 (-.02 to -.01)	-.01 (-.01 to -.01)
Performance	Hiring	High	.1 (.08 to .11)	-.03 (-.05 to -.01)	-.13 (-.15 to -.11)	-.03 (-.04 to -.03)	.01 (0 to .01)	.02 (.01 to .02)
Performance	Hiring	Low	.1 (.09 to .12)	-.01 (-.03 to .01)	-.08 (-.1 to -.06)	-.03 (-.03 to -.02)	.01 (0 to .01)	.01 (.01 to .02)
Voluntary turnover	Layoff	High	0 (-.02 to .02)	-.01 (-.02 to .01)	.01 (0 to .03)	0 (0 to 0)	0 (0 to 0)	0 (0 to 0)
Voluntary turnover	Layoff	Low	0 (-.02 to .02)	-.02 (-.03 to 0)	0 (-.02 to .02)	0 (0 to 0)	0 (0 to 0)	0 (0 to 0)
Voluntary turnover	Dismissal	High	-.04 (-.06 to -.02)	-.03 (-.05 to -.01)	-.01 (-.03 to .01)	0 (-.01 to 0)	0 (0 to 0)	0 (0 to 0)
Voluntary turnover	Dismissal	Low	-.02 (-.05 to 0)	-.01 (-.03 to .01)	.02 (-.01 to .04)	0 (-.01 to 0)	0 (0 to .01)	0 (0 to .01)
Voluntary turnover	Voluntary turnover	High	.01 (-.02 to .04)	.04 (.02 to .06)	.03 (0 to .05)	.01 (0 to .01)	0 (0 to .01)	0 (0 to .01)
Voluntary turnover	Voluntary turnover	Low	.01 (-.01 to .04)	.04 (.02 to .07)	.08 (.05 to .11)	.02 (.01 to .02)	.01 (.01 to .02)	.01 (.01 to .02)
Voluntary turnover	Hiring	High	.05 (.03 to .07)	.01 (-.01 to .03)	0 (-.02 to .02)	0 (0 to .01)	-.01 (-.01 to 0)	-.01 (-.01 to 0)
Voluntary turnover	Hiring	Low	.07 (.05 to .1)	.06 (.03 to .08)	.02 (0 to .05)	.02 (.01 to .02)	0 (0 to .01)	0 (-.01 to 0)

Note. Impulse responses over time to shocks to the variables in the shock column for bottom 40% of collective affective attitude (Level=Low) and top 40% of collective affective attitude (Level=High).
months 7 through 12 are omitted, because the effects decline to zero.

Table 3-11 Moderating Effects of Local Unemployment Rate on the Relationship between Staffing Events and Work Outcomes Over Time

Dependent	Shock	Level	Month1	Month2	Month3	Month4	Month5	Month6
Performance	Layoff	High	-.01 (-.03 to 0)	0 (-.01 to .02)	.01 (0 to .02)	0 (0 to 0)	0 (0 to 0)	0 (0 to .01)
Performance	Layoff	Low	0 (-.01 to .01)	0 (-.01 to .01)	0 (-.01 to .01)	0 (0 to 0)	0 (0 to 0)	0 (0 to 0)
Performance	Dismissal	High	-.04 (-.06 to -.03)	0 (-.01 to .01)	.02 (0 to .03)	0 (0 to .01)	0 (-.01 to 0)	-.01 (-.01 to 0)
Performance	Dismissal	Low	-.02 (-.03 to 0)	.01 (0 to .03)	.02 (.01 to .03)	0 (0 to .01)	0 (-.01 to 0)	0 (-.01 to 0)
Performance	Voluntary turnover	High	-.02 (-.03 to -.01)	-.01 (-.02 to .01)	.03 (.02 to .04)	0 (-.01 to 0)	-.02 (-.02 to -.01)	-.01 (-.02 to -.01)
Performance	Voluntary turnover	Low	-.02 (-.04 to -.01)	-.01 (-.02 to .01)	.04 (.03 to .06)	0 (0 to .01)	-.01 (-.01 to 0)	-.01 (-.01 to 0)
Performance	Hiring	High	.12 (.1 to .13)	-.02 (-.04 to 0)	-.13 (-.15 to -.12)	-.04 (-.04 to -.03)	0 (0 to .01)	.02 (.01 to .02)
Performance	Hiring	Low	.08 (.07 to .1)	-.03 (-.04 to -.01)	-.1 (-.12 to -.09)	-.02 (-.03 to -.02)	.01 (.01 to .01)	.01 (.01 to .02)
Voluntary turnover	Layoff	High	0 (-.02 to .01)	-.01 (-.02 to .01)	0 (-.01 to .02)	0 (-.01 to 0)	0 (0 to 0)	0 (0 to 0)
Voluntary turnover	Layoff	Low	0 (-.02 to .02)	-.01 (-.03 to 0)	.02 (0 to .04)	0 (0 to 0)	0 (0 to 0)	0 (0 to 0)
Voluntary turnover	Dismissal	High	-.04 (-.06 to -.02)	0 (-.02 to .01)	0 (-.02 to .02)	0 (-.01 to 0)	0 (0 to 0)	0 (0 to 0)
Voluntary turnover	Dismissal	Low	-.03 (-.05 to -.01)	-.02 (-.04 to 0)	-.01 (-.03 to .01)	0 (-.01 to 0)	0 (-.01 to 0)	0 (0 to 0)
Voluntary turnover	Voluntary turnover	High	.02 (0 to .04)	.05 (.03 to .06)	.05 (.03 to .07)	.01 (.01 to .02)	.01 (.01 to .02)	.01 (0 to .01)
Voluntary turnover	Voluntary turnover	Low	.03 (0 to .06)	.03 (0 to .05)	.07 (.04 to .09)	.01 (0 to .02)	.01 (0 to .01)	.01 (0 to .01)
Voluntary turnover	Hiring	High	.06 (.04 to .08)	.04 (.02 to .05)	.02 (0 to .04)	.01 (.01 to .02)	0 (0 to .01)	0 (-.01 to 0)
Voluntary turnover	Hiring	Low	.08 (.06 to .1)	.04 (.02 to .06)	0 (-.02 to .02)	.01 (0 to .01)	0 (-.01 to 0)	-.01 (-.01 to 0)

Note. Impulse responses over time to shocks to the variables in the shock column for bottom 40% of local unemployment rate (Level=Low) and top 40% of local unemployment rate (Level=High).
months 7 through 12 are omitted, because the effects decline to zero.

Table 3-12 Cross-lagged relationships among internal context variables and unit engagement

	Model 1 Perceived unit engagement	Model 2 Perceived unit engagement	Model 3 Collective affective attitude
L.Perceived unit engagement	0.82***	0.69***	
	(0.01)	(0.01)	
L.Appreciation ritual participation	0.06***		0.07***
	(0.01)		(0.01)
L.Collective affective attitude		0.20***	0.83***
		(0.01)	(0.01)
Control variables	Yes	Yes	Yes
	Appreciation ritual participation	**Collective affective attitude**	**Appreciation ritual participation**
L.Appreciation ritual participation	0.79***		0.77***
	(0.01)		(0.01)
L.Perceived unit engagement	0.04***	0.30***	
	(0.01)	(0.01)	
L.Collective affective attitude		0.62***	0.07***
		(0.01)	(0.01)
Control variables	Yes	Yes	Yes
Observations	3540	5612	11228

Note. Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. L. stands for lagged, representing one month lagged variable.

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